Artificial Intelligence Literacy

Conceptualization, Measurement, Enablement, and Its Impact on Individuals and Organizations

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Abstract

Advancements in technology continually redefine what it means to be technologically literate in contemporary society and the business world. The recent surge in artificial intelligence (AI) technologies has particularly catalyzed this transformation, necessitating a reevaluation of existing technology literacy concepts. While AI technologies have achieved astonishing capabilities, they also have unique facets that distinguish them from prior technology, such as their inscrutability. These dynamics have prompted researchers in Information Systems (IS) and related disciplines to delve into the topic of AI literacy, investigating what it means to be literate concerning this new class of technologies. AI literacy refers to a holistic human proficiency in a variety of subject areas concerning AI that enable purposeful, efficient, and ethical usage of AI technologies. However, our current understanding of this new form of literacy is still quite limited. Since AI as a phenomenon is not only technologically different from prior technology but also has distinct sociological and psychological effects on humans, it remains unclear what such a new AI literacy concept needs to entail to prepare humans for the efficient and responsible usage and management of these technologies. Moreover, little research exists on the specific effects of AI literacy on humans and organizations, which is crucial to improving human-AI interactions and collaborations.

Therefore, this dissertation aims to comprehend AI literacy and its ramifications for individuals and organizations by asking three overarching research questions. First, it asks how AI literacy can be conceptualized, measured, and enabled, laying the foundation for further AI literacy research. Second, it ventures into the effects of AI literacy on individual humans, specifically, asking how it affects their AI-related cognition (e.g., AI-related intentions and attitudes) and behavior (e.g., AI delegation behavior) in human-AI collaborations and interactions. Third, it examines the effects of AI literacy on organizations, specifically probing how the AI literacy of top management teams (TMTs) affects their organizations' AI strategy and implementation. To answer these three research questions, this thesis draws on five research articles.

The first article contributes to answering the first research question by focusing on conceptualizing AI literacy for users. It conducts a systematic literature review to synthesize existing knowledge and develops a conceptual framework for AI literacy. Through this framework, the article identifies six subject areas and five proficiency dimensions of AI literacy, providing insights into users' required literacy for the purposeful, efficient, and ethical usage of AI technologies. Moreover, it identifies and structures the existing research regarding the different learning methods to acquire AI literacy as well as the effects of AI literacy that have been discovered so far.

Continuing with addressing the first research question, the second article aims to develop a measurement instrument for assessing individuals' AI literacy. Following established scale development procedures, it conducts a systematic literature review, expert interviews, and a validation study to create a measurement model containing five dimensions and 13 items. The study provides empirical support for the proposed measurement model and validates the instrument for assessing individuals' AI literacy levels.

The third article addresses both the first and the second research questions. Drawing on a design science research approach, it designs an AI literacy learning experience and evaluates its effects on human cognition. The developed learning experience, a mobile learning application, "AiLingo," targets non-expert adults to help them enhance their AI literacy. As such, it provides an enablement tool for AI literacy, completing the answer to the first research question. Moreover, the study evaluates the learning application through a between-subjects experiment. The results show that the learning experience leads to greater AI literacy advancement than a control learning experience, validating the ability to enable AI literacy efficiently, as well as that AI literacy positively influences AI-related intentions and attitudes, which addresses the second research question. From a scientific point of view, the developed design artifact (i.e., the mobile learning application) can also be viewed as a manipulation instrument, which future studies can utilize.

The fourth article also addresses the second research question and focuses on how AI literacy affects human behavior in human-AI collaborations, particularly focusing on delegation decisions. It shows through a between-subjects experiment in the image classification context that AI literacy training improves humans' delegation decisions, leading to better task performance. The findings have implications for design guidelines of human-AI collaboration, emphasizing the role that potential educational features about AI functioning and human biases could have.

Last, the fifth article addresses the third research question, exploring how the

AI literacy of TMTs (TMT AI literacy) influences strategic AI orientation and implementation ability of organizations. Drawing on upper echelons theory, it analyzes observational data from executives' LinkedIn profiles and firm data from 10-k statements to demonstrate that TMT AI literacy positively impacts a firm's AI orientation and implementation ability. Moreover, it uncovers a moderating effect of the type of the respective firm (startup vs. incumbent) on the effect of TMT AI literacy on AI implementation ability.

These five articles collectively contribute to a comprehensive understanding of AI literacy. By conceptualizing, measuring, and enabling AI literacy, as well as exploring the effects of AI literacy for individuals and organizations, they provide valuable insights into fostering effective and responsible engagement with AI technologies in diverse contexts. From enhancing individual competencies to influencing organizational strategies, AI literacy emerges as a pivotal factor in navigating the complexities of human-AI collaborations and maximizing the value of AI technologies for humans.

Zusammenfassung

Der technologische Fortschritt definiert kontinuierlich neu, was es bedeutet in der heutigen Gesellschaft und in der Geschäftswelt technologisch kompetent (engl. "literate") zu sein. Der jüngste Aufschwung der Technologien der künstlichen Intelligenz (KI) hat diesen Wandel besonders beschleunigt und eine Neubewertung der bestehenden Konzepte für technologische Kompetenz (engl. "Literacy") erforderlich gemacht. KI-Technologien haben zwar erstaunliche Fähigkeiten erlangt, weisen aber auch einzigartige Aspekte auf, die sie von früheren Technologien unterscheiden, wie etwa ihre Undurchsichtigkeit. Diese Dynamik hat Forscher in der Wirtschaftsinformatik und verwandten Disziplinen dazu veranlasst, sich mit dem Thema der KI-Kompetenz (engl. "AI Literacy") zu befassen und zu untersuchen, was es bedeutet, im Umgang mit dieser neuen Klasse von Technologien kompetent zu sein. KI-Kompetenz bezieht sich auf eine ganzheitliche menschliche Befähigung in verschiedenen Themenbereichen der KI, die eine zielgerichtete, effiziente und ethische Nutzung von KI-Technologien ermöglicht. Unser derzeitiges Verständnis dieser neuen Form von Kompetenz ist jedoch noch recht begrenzt. Da sich KI als Phänomen nicht nur technologisch von früheren Technologien unterscheidet, sondern auch signifikante neue soziologische und psychologische Auswirkungen auf den Menschen hat, bleibt unklar, was ein solches neues Konzept der KI-Kompetenz beinhalten muss, um die Menschen auf die effiziente und verantwortungsvolle Nutzung und Verwaltung dieser Technologien vorzubereiten. Darüber hinaus gibt es nur wenig Forschung zu den spezifischen Auswirkungen von KI-Kompetenz auf Menschen und Organisationen, was für die Weiterentwicklung von Mensch-KI-Interaktionen und -Kollaborationen entscheidend ist.

Daher zielt diese Dissertation darauf ab, die KI-Kompetenz und ihre Auswirkungen auf Individuen und Organisationen zu verstehen, indem sie drei übergreifende Forschungsfragen stellt. Erstens geht es um die Frage, wie KI-Kompetenz konzeptualisiert, gemessen und erworben werden kann, um so die Grundlage für weitere KI-Kompetenzforschung zu schaffen. Zweitens werden die Auswirkungen der KI-Kompetenz auf den einzelnen Menschen untersucht, insbesondere die Frage, wie sie

sich auf die KI-bezogene Kognition (z.B. KI-bezogene Absichten und Einstellungen) und das Verhalten (z.B. KI-Delegationsverhalten) in der Zusammenarbeit und Interaktion zwischen Mensch und KI auswirkt. Drittens werden die Auswirkungen der KI-Kompetenz auf Organisationen untersucht, insbesondere wie die KI-Kompetenz des Top-Management-Teams die KI-Strategie und -Implementierung ihrer Organisation beeinflusst. Um diese drei Forschungsfragen zu beantworten, stützt sich diese Arbeit auf fünf Forschungsartikel.

Der erste Artikel trägt zur Beantwortung der ersten Forschungsfrage bei, indem er sich auf die Konzeptualisierung von KI-Kompetenz für Nutzer konzentriert. Er führt eine systematische Literaturrecherche durch, um das vorhandene Wissen zusammenzufassen, und entwickelt einen konzeptionellen Rahmen für KI-Kompetenz. Anhand dieses Rahmens werden sechs Themenbereiche und fünf Kompetenzdimensionen der KI-Kompetenz identifiziert, die einen Einblick in die Kompetenz von Nutzern geben, die für die zweckmäßige, effiziente und ethische Nutzung von KI-Technologien erforderlich ist. Darüber hinaus identifiziert und strukturiert er die bestehende Forschung zu den verschiedenen Lernmethoden zum Erwerb von KI-Kompetenz sowie zu den bisher entdeckten Auswirkungen von KI-Kompetenz.

Zur weiteren Beantwortung der ersten Forschungsfrage zielt der zweite Artikel auf die Entwicklung eines Messinstruments zur Beurteilung der individuellen KI-Kompetenz ab. In Anlehnung an etablierte Skalenentwicklungsverfahren werden eine systematische Literaturrecherche, Experteninterviews und eine Validierungsstudie durchgeführt, um ein Messmodell mit fünf Dimensionen und 13 Items zu erstellen. Die Ergebnisse der Studie zeigen die empirische Validität des vorgeschlagenen Messmodels und -instruments zur Bewertung der KI-Kompetenz von Individuen.

Der dritte Artikel behandelt sowohl die erste als auch die zweite Forschungsfrage. Auf der Grundlage eines design-orientierten Forschungsansatzes ("Design Science Research") wird eine Lernerfahrung für KI-Kompetenz entwickelt und ihre Auswirkungen auf die menschliche Kognition untersucht. Die entwickelte Lernerfahrung, eine mobile Lernanwendung, "AiLingo," richtet sich an erwachsene Nicht-Experten und soll ihnen helfen, ihre KI-Kompetenz zu verbessern. Als solches stellt die Lernanwendung ein Werkzeug zur Förderung der KI-Kompetenz dar und vervollständigt damit die Antwort auf die erste Forschungsfrage. Darüber hinaus evaluiert die Studie die Lernanwendung durch ein Gruppenvergleichsexperiment. Die Ergebnisse zeigen, dass die Lernerfahrung zu größeren Lernfortschritten bei der KI-Kompetenz führt als eine Kontroll-Lernerfahrung. Dies bestätigt, dass die Lernerfahrung die KI-Kompetenz effizient steigern kann, sowie dass die KI-Kompetenz die KI-bezogenen Absichten und Einstellungen positiv beeinflusst, was einen Teil der zweiten Forschungsfrage beantwortet. Zudem kann das entwickelte Design-Artefakt (d.h. die mobile Lernanwendung) aus wissenschaftlicher Sicht auch als Manipulationsinstrument betrachtet werden, das in zukünftigen Studien eingesetzt werden kann.

Der vierte Artikel befasst sich ebenfalls mit der zweiten Forschungsfrage und konzentriert sich darauf, wie die KI-Kompetenz das menschliche Verhalten in der Mensch-KI-Kollaboration beeinflusst, wobei der Schwerpunkt auf Delegationsentscheidungen liegt. Anhand eines Gruppenvergleichsexperiments im Kontext der Bildklassifizierung wird gezeigt, dass das Training von KI-Kompetenz die Delegationsentscheidungen von Menschen verbessert und zu einer besseren Aufgabenleistung führt. Die Ergebnisse haben Auswirkungen auf die Gestaltungsrichtlinien für die Zusammenarbeit zwischen Mensch und KI, indem sie die Rolle hervorheben, die potenzielle Trainingsfeatures zur Funktionsweise von KI und menschlichen Wahrnehmungsverzerrungen haben könnten.

Der fünfte Artikel befasst sich mit der dritten Forschungsfrage und untersucht, wie die KI-Kompetenz von Top-Management-Teams (TMTs) die KI-Orientierung und -Umsetzungsfähigkeit von Unternehmen beeinflusst. Unter Rückgriff auf die Upper Echelons Theorie werden Beobachtungsdaten aus LinkedIn-Profilen von Führungskräften und Unternehmensdaten aus 10-k-Abschlussberichten analysiert, um zu zeigen, dass sich die KI-Kompetenz von TMTs positiv auf die KI-Orientierung und -Umsetzungsfähigkeit von ihren Unternehmen auswirkt. Darüber hinaus wird ein moderierender Effekt der Art des jeweiligen Unternehmens (Startup vs. etabliertes Unternehmen) auf den Effekt der KI-Kompetenz von TMTs auf die KI-Umsetzungsfähigkeit festgestellt.

Diese fünf Artikel tragen gemeinsam zu einem umfassenden Verständnis von KI-Kompetenz bei. Indem sie KI-Kompetenz konzeptualisieren, messen und den Erwerb ermöglichen sowie die Auswirkungen von KI-Kompetenz auf Individuen und Organisationen untersuchen, bieten sie wertvolle Einblicke in die Förderung eines effektiven und verantwortungsvollen Umgangs mit KI-Technologien in unterschiedlichen Kontexten. Von der Verbesserung individueller Kompetenzen bis hin zur Beeinflussung organisationalen Strategien erweist sich KI-Kompetenz als zentraler Faktor, um die Komplexität der Zusammenarbeit zwischen Mensch und KI zu bewältigen und den Wert von KI-Technologien für Menschen zu maximieren.

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List of Abbreviations

Abbreviation	Meaning
ABV	Attention-based View of the Firm
ACM	Association for Computing Machinery
ACME	Average Causal Mediation Effect
ADE	Average Direct Effect
AI	Artificial Intelligence
AIO	AI Orientation
AIL	AI Literacy
AIS	Association for Information Systems
AK	AI Actor Knowledge
AUCI	AI Usage Continuance Intentions
AVE	Average Variance Extracted
CA	Cronbach's Alpha
CAM	Computer-aided Manufacturing
CCS	Computing Classification System
CED	Computer Education
CIO	Chief Information Officer
CR	Composite Reliability
CRM	Client Relationship Management
CTO	Chief Technology Officer
DE	AI Design Experience
DF	Design Feature
DP	Design Principles
DSR	Design Science Research
DV	Dependent Variable
e.g.	Exempli Gratia / for example
ERP	Enterprise Resource Planning
EX	AI Experience
FT	Firm Type
GPT	Generative Pre-trained Transformer
HAIIA	HR-related AI Implementation Ability

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Abbreviation	**Meaning**
HCI	Human-Computer Interaction
HITIA	IT-related AI Implementation Ability
HK	Human Actor in AI Knowledge
HR	Human Resources
i.e.	Id Est / that is
IIO	IT Orientation
IK	AI Input Knowledge
IS	Information Systems
IT	Information Technology
IV	Independent Variable
JEL	Journal of Economic Literature
M	Average
MD&A	Management Discussion and Analysis
MIS	Management Information System
ML	Machine Learning
NAICS	North American Industry Classification System
OK	AI Output Knowledge
OLS	Ordinary Least Squares
p	P-Value
PK	AI Processing Knowledge
pp	Percentage Point
R&D	Research and Development
RQ	Research Question
SCM	Supply Chain Management
SD	Standard Deviation
SDT	Self-determination Theory
SEM	Structural Equation Model
SK	AI Steps Knowledge
T	Time
TE	Total Effect
TK	AI Technology Knowledge
TMT	Top Management Team
UE	AI Usage Experience
UET	Upper Echelons Theory
VHB	Verband der Hochschullehrerinnen und Hochschullehrer für Betriebswirtschaft
VIF	Variance Inflation Factor

Artificial Intelligence Literacy

1 Introduction

1.1 Motivation and Research Questions

> *“New technologies regularly and repeatedly transform previous literacies, continually redefining what it means to become literate.”* (Leu et al., 2013)

Humans have always required a specific literacy to use and manage information technology effectively and responsibly (Leu et al., 2013). This technology literacy extends significantly beyond the original meaning of literacy as reading and writing abilities (D. R. Moore, 2010). Moreover, it is subject to constant social and technological developments, inducing more or less significant changes over time (Leu et al., 2004, 2013). In recent years, technologies based on artificial intelligence (AI) have reached an unprecedented pace of development, enabling it to make astonishing leaps concerning its capabilities (Jain et al., 2021). These capability leaps and their implications prompted information systems (IS), human-computer interaction (HCI), and computer education (CED) researchers to devote significant attention to AI literacy, evaluating what it means to be literate concerning these new technologies based on AI (e.g., Cetindamar et al., 2022; Heyder and Posegga, 2021; Ng et al., 2021). However, to understand and explore AI literacy, it is necessary to first understand how AI technology differs from prior technology.

The attention drawn to AI overall – a concept originally dating back to the 1950s (McCarthy et al., 1955; Turing, 1950) – has been revitalized by a massive increase in computing power as well as technological breakthroughs, such as the transformer technology underlying modern large language models (Vaswani et al., 2017). These and other factors allowed the capability leaps of AI technologies, such as achieving unprecedented accuracies in tasks like classification, being able to process unstructured data that prior technology was unable to process, or enabling effortless interactions in natural human language (Q. N. Nguyen et al., 2022; Schuetz & Venkatesh, 2020). As a result, AI technologies permeate various aspects of society and business, for example, by curating social media feeds of individuals or enabling predictive maintenance for organizations (M. Weber et al., 2022). With the advent of generative AI, a class of AI technology also capable of creating content like texts, images, sound, or videos, academics and practitioners expect AI to unlock further economic potential and penetrate society and businesses even more (Brynjolfsson et al., 2023; B. Peng et al., 2023).

While AI technologies have astonishing capabilities, they are governed by different principles compared to prior (non-AI) technologies, leading to unique facets like inscrutability (Berente et al., 2021). These facets significantly affect the relationship between humans and technology because they invalidate certain assumptions held about technology for a long time, like functional consistency and transparency (Schuetz & Venkatesh, 2020). Moreover, AI as a phenomenon is not only technologically different from prior technology but also has distinct sociological and psychological effects on humans (Sundar, 2020). For example, by comprising the notion of "intelligence," which even experts define in a variety of different ways, many non-experts are led to ascribe qualities to AI technology, which it has by far not achieved yet (Diederich et al., 2022; Kapania et al., 2022). Moreover, the media often speculates about potential dystopian futures with AI (Benlian et al., 2022; Long & Magerko, 2020; Willcocks, 2020). As such, both the new technological capabilities of AI and the social dynamics it induces have a significant potential to affect how humans interact and collaborate with technology. However, we are only beginning to understand the implications for humans and their organizations (Adam et al., 2023; Teodorescu et al., 2021). Recent studies have shown that AI technologies can affect humans who interact and collaborate with them in unforeseen ways, like resulting in a loss of unique human knowledge (Fügener et al., 2021b) or expressing a general aversion towards AI in some contexts and a general appreciation in others (Berger et al., 2020; Schecter et al., 2023; You et al., 2022). Moreover, incidents in the real world have shown that AI technologies can produce unwanted outcomes in organizations, such as an AI from the company Amazon that made personnel decisions that discriminated against women (Dastin, 2018).

To address these challenges, much research has focused on how features of AI technologies, such as approaches aiming to make AI decisions explainable, can improve human-AI collaborations (Leichtmann et al., 2023; Yuan et al., 2023). On the contrary, we know relatively little about the human factors at play (Long & Magerko, 2020). Looking at prior technologies, many assume that to use and manage AI technologies effectively and responsibly, as well as to realize the economic potential of AI technologies, humans will need AI literacy (Leu et al., 2013; World Economic Forum, 2022b). In the context of individuals, AI literacy might equip humans collaborating with AI with the necessary judgment abilities to assess when to rely on AI (Leana, 1986). In an organizational context, an AI-literate management team might make better decisions about where and how AI technologies can create value in a business (Jorzik et al., 2023). However, while AI literacy promises significant potential, we do not yet fully understand it and have little empirical evidence on what it means to be AI-literate. As such, there is a need to investigate what AI literacy comprises and how it can be conceptualized and operationalized (i.e., measured and enabled) in order to be able to examine how it affects individuals collaborating with AI as well as organizations intending to adopt AI. Such an understanding would add to the set of levers we can draw on to improve the usage and management of AI technologies.

Regarding our understanding of what AI literacy comprises, researchers started to review and organize individual competencies relevant to evaluating, using, and critically assessing AI, for example, the ability to recognize AI when interacting with it (e.g., Long and Magerko, 2020; Ng et al., 2021). However, a comprehensive understanding, including the respective measurement and enablement instruments, has not yet emerged. As such, this dissertation formulates a first research question primarily in order to build a clear understanding of what AI literacy refers to as well as to operationalize the construct for further investigation to quantify the effects of AI literacy:

RQ1: How can AI literacy be conceptualized, measured, and enabled?

Once one has conceptualized the construct of AI literacy and is able to measure and enable it, the prerequisites for investigations concerning its effects on individuals and organizations are fulfilled. Examining how AI literacy unfolds in both contexts in greater depth is paramount for a better understanding of how to design and adopt AI technologies that function as we envision them. Therefore, this dissertation will examine the individual human context, shedding light on how an individual's AI literacy affects them in their private and work life, and then investigate the organizational context, exploring how a team's AI literacy from an organization affects AI-related characteristics of their organization. Regarding the latter, the thesis focuses specifically on the top management teams (TMT) of organizations, as they play a crucial part in the adoption of AI by being the responsible entities for defining an AI ambition, committing resources, and setting the framework for others in the adoption process (Jorzik et al., 2023).

Individual humans already interact or collaborate – knowingly or unknowingly – with many AI technologies at various points in their private and work lives. In their private lives, individuals interact with AI technologies when they receive recommendations for products, news, or entertainment, or, more recently, also when using applications, such as DeepL (translation app), ChatGPT (text generation app), or Midjourney (image generation app) (Fui-Hoon Nah et al., 2023; J. Zhang et al., 2020). In work-related settings, individuals may collaborate with AI, such as medical doctors working with AI diagnosis tools (Jussupow et al., 2021; Lebovitz et al., 2022) or software developers aided by AI pair programmers (S. Peng et al., 2023). While AI technologies already exceed human capabilities in many regards and will continue to improve, there are many settings where human collaboration will also be necessary in the future from an ethical point of view or where fully autonomous AI is prohibited or regulated (e.g., EU AI Act, European Commission, 2021). Therefore, the prevalence of human-AI collaborations will significantly rise in the future.

To gain a better understanding of AI literacy's role in human-AI interactions and collaborations, human cognitions and behavior are two particularly relevant types of outcomes (Chiang & Yin, 2022; Chiang et al., 2023; W. Yang, 2022). Human cognitions refer to the mental models a human might have concerning AI technologies (Kapania et al., 2022), their future usage intentions (Bhattacherjee, 2001), or their general attitudes towards it (Schepman & Rodway, 2022). Such human cognitions influence whether humans are willing to interact and stay in human-AI collaborations (Chiu et al., 2021). While researchers have started to investigate human cognitions in human-AI collaborations (e.g., Jussupow et al., 2021), we lack insights into how AI literacy impacts these. Moreover, not only human cognitions are relevant when assessing human-AI interactions and collaborations but also human behavior. When humans hold the ultimate decision power in collaborative work settings, their behavior (e.g., the delegation of specific tasks to an AI) is a critical determinant of the joint human-AI performance or compliance with ethical guidelines (Fügener et al., 2021a; Lai et al., 2022). Prior studies examined, for example, how a group vs. individual setting (Chiang et al., 2023) or how explainable AI features (Leichtmann et al., 2023) affect behavior and, consequently, the performance of human-AI collaborations. However, there are still many uncharted aspects of human-AI collaborations, like the relationships between AI literacy and human cognition and behavior, where only some initial research has been conducted (e.g., Chiang and Yin, 2022). Yet, insights into such associations would have a direct impact on improving such collaborations. Therefore, this dissertation formulates a second research question addressing AI literacy's effects in the context of the human individual:

RQ2: How does the AI literacy of individuals affect their AI-related cognition and behavior in human-AI collaborations in their private and professional lives?

Understanding how AI literacy affects individual humans is crucial to improving our understanding of the underlying mechanisms in individual human-AI interactions and collaborations. However, the decisions on whether AI is adopted at all and in which form are often made by organizations, such as firms, schools, or governments. To complement the investigation of how AI literacy unfolds for individuals, this dissertation also sheds light on how AI literacy contributes to the adoption of AI technologies to begin with. Within organizations, the TMT is often a pivotal entity for AI adoption, as TMTs are responsible for ensuring sustained value creation (e.g., by leveraging new technology), granting necessary resources, and setting the overall direction of the organization (Berente et al., 2021; Jorzik et al., 2023). Therefore, this thesis explores how the AI literacy of a TMT (TMT AI literacy) affects their organization's AI adoption. Organizations are urged to adopt AI technologies (like any other technology) because they generate a specific value (Shollo et al., 2022), such as economic value for a business, educational value for a school, or societal value for a government. Adopting AI technology to generate value requires an organization first to identify a value potential and then second to realize the value. Prior studies have identified two organizational characteristics that can be utilized to assess and investigate this value-generating AI adoption process: First, to identify the value potentials of AI, a company must develop a thorough strategic AI orientation, which is its overall strategic direction and the objectives it has for introducing AI technology (J. Li et al., 2021). Second, it needs, among other factors, AI implementation ability, which refers to the capabilities necessary to execute the strategic direction and realize the identified AI value potential (M. Weber et al., 2022). While these two characteristics for AI adoption in organizations – a thorough AI orientation followed by implementation – have been described by academics and practitioners (Chatterjee et al., 2022; J. Li et al., 2021; Mikalef & Gupta, 2021), broad empirical evidence specifically on how they can be achieved is still lacking. The AI literacy of an organization's TMT promises great potential to foster these characteristics and, ultimately, AI adoption to generate positive value with the technology (Jorzik et al., 2023). Therefore, this dissertation formulates a third research question addressing AI literacy in the organizational context:

RQ3: How does the AI literacy of top management teams affect their organization's strategic AI orientation and AI implementation?

To answer these three research questions, my co-authors and I conducted five studies that we published in peer-reviewed IS as well as HCI journals and conference proceedings. The first study developed a conceptualization of AI literacy via a systematic literature review. Thereafter, studies two and three developed an AI literacy measurement instrument and a learning experience to enable AI literacy. Together these three articles address RQ1 by providing a conceptualization and operationalization of the construct of AI literacy. Moreover, the third study also investigated the effects of AI literacy on human cognition, specifically humans' continuance intentions and attitudes concerning AI technology. The fourth study shed light on the effects of AI literacy on human behavior, more precisely, the delegation behavior of humans to AI in human-AI collaborations. The third study and the fourth study are both situated in the context of the individual and together address RQ2, providing insights into the relationships between individuals' AI literacy and their cognition and behavior. Complementary to this is the fifth study, which is situated in the organizational context and focuses on the AI literacy of TMTs and its effects on AI-related characteristics of their organizations, thus addressing RQ3. Taken together, the five studies lay the groundwork for conceptualizing, measuring, and enabling AI literacy, followed by an investigation of its effects in the individual as well as organizational context.

1.2 Theoretical Foundations

This section establishes the foundations for this cumulative dissertation by introducing the theoretical background as well as the research contexts of the individual research articles. Since this thesis investigates on different analytical levels (individual and organizational), it draws on multiple theoretical lenses. Furthermore, the section situates this dissertation in prior research. To do so, it first provides an overview of technology literacy research, including prior literacy concepts and the need for AI literacy, thereby, reviewing the genesis of AI literacy as a concept (Subsection 1.2.1). To provide a background for the enablement of AI literacy, the second subsection expands on prior research concerning AI literacy learning experiences as well as the self-determination theory as the underlying foundation for explaining human learning (Subsection 1.2.2). The third subsection relates to AI literacy's effects in the human individual context (Subsection 1.2.3). Drawing on cognitive appraisal theory, it introduces the theoretical foundations for explaining human behavior and cognition in human-AI collaboration. Lastly, we expound upon the significance of AI literacy in the context of organizational management (Subsection 1.2.4). Therefore, the fourth subsection introduces the upper echelons theory as a scaffolding to explain AI literacy's effects on organizational characteristics like strategic AI orientation and implementation ability.

1.2.1 Technology Literacy Research

1.2.1.1 Prior Concepts and the Notion of Literacy

Prior technology literacy research conceptualized different specialized literacies tailored to particular aspects of technology. Among the most prominent concepts are digital literacy (Gilster, 1997; Neumann et al., 2016), data literacy (Ongena, 2023; Wolff et al., 2016), and media literacy (Livingstone, 2004; Potter, 2013). Digital literacy has been described as a "large variety of complex cognitive, motor, sociological, and emotional skills, which users need in order to function effectively in digital environments" (Eshet-Alkalai, 2004, p. 1). Studies emphasize that digital literacy empowers humans to use technology responsibly and ethically (Feerrar, 2019; Njenga, 2018). With the rising relevance not only of digital technology itself but also of the data that feeds into the technology, researchers conceptualized data literacy (Ongena, 2023; Wolff et al., 2016). This form of literacy also comprises knowledge and skill components, such as data analysis techniques (Kerpedzhiev et al., 2020), ethical and critical judgment components (Someh et al., 2019), as well as an understanding of how data influences society (Wolff et al., 2016). Media literacy describes the competent navigation around information from different sources in a digital space, which also necessitates not only knowledge of different media but also the ability to critically assess content as well as a certain drive to search and validate information (Potter, 2004, 2013).

Common to these technology literacy concepts is that they describe a state that goes beyond individual skills or bits of knowledge. Instead, the larger technology literacy notion describes a fundamental, holistic, and enabling proficiency of humans that not only allows one to use technology productively but also allows one to evaluate technology within its social context. Therefore, it is integral for technology literacy concepts to include ethical considerations, responsible behavior, and critical appraisal, which ensure that individuals engage with technology conscientiously and morally. This perspective is underlined by the World Economic Forum (2018, 2020), arguing that a broader range of abilities, such as analytical thinking, active self-driven learning, and (global) citizenship, have replaced technology-centered skills in daily life and employment with technology. Moreover, it aligns with the socio-technical perspective, which constitutes a key viewpoint in IS research (Sarker et al., 2019). Overall, the notion of literacy concerning technology in prior literature can be described as a holistic construct of human proficiency enabling humans to reflect and use technology purposefully, productively, and responsibly.

1.2.1.2 Artificial Intelligence and the Need for AI Literacy

The concepts reviewed above were sufficient to describe the human proficiency necessary for technology usage and management for the last decades. However, already during the advent of digitalization in the early 2000s, Leu et al. (2004) noted that technology literacy is subject to constant change. The recent developments of AI significantly contribute to the force driving this change and the need for a revised literacy understanding. However, before one can analyze the implications of AI for technology literacy, it is necessary to review the term AI in greater detail. AI is a diffuse concept in the current discourse, and different scholars have proposed various definitions of AI (Collins et al., 2021). For example, Duan et al. (2019, p. 1) define AI as the "ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks." G. Rana and Sharma (2019, p. iii) propose an even broader view of AI as the "ability of a machine to perform cognitive functions that we associate with human minds [...]." Like these two definitions, many scholars define AI in relation to humans (Collins et al., 2021). Another definition by Berente et al. (2021, p. 1435) makes this explicit as they refer to AI as "the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems." Moreover, Berente et al. (2021) conceptualize three facets of AI that build on their definition: autonomy, learning, and inscrutability. These three facets constitute a purposeful analytical lens to distinguish AI technology from non-AI technology and to discern the need for AI literacy.

Autonomy refers to the fact that AI technologies are increasingly capable of operating without human intervention (Baird & Maruping, 2021), for example, as automated investment advisors (I. Lee & Shin, 2018) or AI-driven loan underwriters (Markus, 2017). Learning expresses that the technology can improve automatically over time (Janiesch et al., 2021). This facet enables AI to solve complex tasks, such as object recognition or the generation of different media (Brynjolfsson et al., 2023). Inscrutability describes that the nature of the technological design makes it impossible for humans to comprehend how (some of) the technologies derive their decisions (Brasse et al., 2023).

These facets invalidate different fundamental assumptions of human-technology interaction, which makes new human competencies, skills, and knowledge necessary

(Schuetz & Venkatesh, 2020). For example, the autonomy facet breaks the assumption that technology has an artificial interface (Schuetz & Venkatesh, 2020). Voice assistants like Siri or chatbots in customer service enable interaction in natural language. Therefore, humans increasingly need the skill to recognize that they interact with technology (Long & Magerko, 2020). The learning facet breaks the assumption that technology is functionally consistent because the same technology can behave differently over time once it has learned through new data (Berente et al., 2021). Such behavior necessitates new knowledge when interacting with a technology that can learn. Humans have been shown to quickly lose trust in technology when it has erred once (Berger et al., 2020). This might be inappropriate with an AI technology that has learned from its errors. The inscrutability facet breaches the functional transparency assumption of technology (Schuetz & Venkatesh, 2020). When decisions of a specific technology cannot be explained anymore, the humans utilizing this technology need the skill to assess when and how it is advisable to use it and which measures to take before implementing it (Laupichler, Aster, Haverkamp, & Raupach, 2023).

The three AI facets make it apparent that human-technology interaction has changed in manifold ways. These altered interaction mechanisms combined with the increasing adoption of AI show why prior technology literacy concepts must be extended and why AI literacy needs to be explored. In other words, humans must develop AI literacy to understand and react to the current paradigm shift of human-technology interaction.

1.2.2 AI Literacy Enablement

Learning experiences are a central instrument to enable humans with AI literacy (Long, Padiyath, et al., 2021; Zhou et al., 2020). To design a purposeful AI literacy learning experience, an understanding of the prevailing learning experience types and the theoretical underpinning explaining learning motivation is necessary. The literature generally distinguishes learning experiences into two types: formal and informal learning (Folkestad, 2006; Manuti et al., 2015). Formal learning is characterized by structured, planned activities typically conducted in classroom-based settings (Marsick & Watkins, 2001). It adheres to the conventional educational paradigm with designated teachers, prescribed qualifications, and external outcome specifications (Eraut, 2000). Conversely, informal learning, often described as learning that is non-formal (Colley et al., 2002), encompasses learning that occurs spontaneously, for example, within daily activities (Marsick & Watkins, 2001). It is an unconscious process that can be influenced by chance and involves a cyclical pattern of reflection and action, closely intertwined with learning from others (Marsick & Watkins, 2001). Both types of learning experiences have been developed for AI literacy, such as university courses (formal) (e.g., Kandlhofer et al., 2016) or museum exhibits (informal) (e.g., Long, Blunt, and Magerko, 2021), with a stronger emphasis on formal learning experiences within the existing literature. However, especially for non-experts, who are increasingly confronted with AI and human-AI collaborations in their private and professional life, informal learning experiences are key to keeping up-to-date with the literacy necessary for the recent developments of AI.

When investigating and designing such learning experiences, many studies use the self-determination theory as a theoretical underpinning to explain and foster the motivation to learn (Sailer & Homner, 2019; Tyack & Mekler, 2020). Self-determination theory posits three key factors - competence, autonomy, and relatedness - that stimulate intrinsic motivation in learning activities (Deci & Ryan, 1985). Firstly, competence entails learners' perceptions of their effectiveness in achieving set goals, facilitated by appropriate tasks and feedback (Ryan & Deci, 2000). Secondly, autonomy emphasizes the importance of learners' self-directedness and initiative in the learning process, highlighting the detrimental effects of excessive control on learning outcomes (Ryan & Deci, 2000). Lastly, relatedness underscores the significance of a sense of belongingness and connection to others in motivating engagement in learning activities (Ryan & Deci, 2000). Whether it is affiliation with peers, teachers, or broader societal groups, feeling connected encourages the internalization of learning goals and fosters proactive participation in learning endeavors (Ryan & Deci, 2000). Utilizing these three SDT factors can help to design more successful AI literacy learning experiences.

Enablement of humans with the appropriate AI literacy remains a key challenge, which is, on the one hand, scientifically relevant to conduct sound experiments on the effects of AI literacy and, on the other hand, also practically relevant to inform educators how they can convey AI-specific content most effectively. Moreover, designers of human-AI collaborations can utilize the knowledge concerning AI literacy enablement to design educational features integrated into AI technologies themselves.

1.2.3 Individual Lens: AI-related Human Cognition and Behavior in Human-AI Interactions and Collaborations

Interactions and collaborations between humans and AI technology follow different dynamics than between humans and prior technology (Schuetz & Venkatesh, 2020). To improve how we interact and collaborate subject to these new dynamics, it is paramount to understand how humans are affected during these interactions and collaborations. Humans' cognitive states and processes ("cognitions") and behaviors are two potentially affected factors that are of particular relevance for the successful deployment of AI. Human behavior (e.g., delegation) could determine overall performance (Fügener et al., 2021a), while human cognitions (e.g., attitude towards AI) could induce fear of AI, also impacting performance (Sindermann et al., 2020). By centering on the AI literacy of the individual, this dissertation intends to increase our understanding of how humans are affected and how we might mitigate or foster such (un)desired effects.

A central theory aimed at explaining human responses to stimuli, such as interactions with an AI, is the cognitive appraisal theory (Beaudry & Pinsonneault, 2005; Folkman, 2013). The theory introduces two factors determining, in general, how a human responds to a particular situation: the attributes of the human, such as their literacy, beliefs, or values, and their perception of the situation (Lazarus & Folkman, 1984). In this context, Folkman (2013) defines appraisal as evaluating how a situation evolves in relation to the human's goals. Applied to a collaboration or interaction setting, like human-AI collaboration, it translates into a human assessing their own attributes (including their domain knowledge, AI literacy, etc.) and the situation (including the task, technology, etc.) to pursue their goals, which in turn determines their cognitions and behaviors. For example, a human might work with an AI to which they can delegate tasks (e.g., a medical diagnosis decision based on an image). In such a delegation-based setting, the perception of the situation can be further broken down into perceptions of the subordinate (i.e., the AI) and other situational characteristics (e.g., the task) (Baird & Maruping, 2021; Leana, 1986; Yukl & Fu, 1999). Then, to pursue the goal of solving the task correctly, appraisal can be seen as a human's assessment of the fit of their attributes compared with the AI's attributes for the given task, which consequently guides their delegation behavior. However, human goals, in that sense, are not limited to a task context. Humans might have other goals that also determine their cognitions. For example, given a human's goal of staying relevant or retaining their position, appraisal of an AI might result in a replacement fear (Sindermann et al., 2020), which could affect their attitudes and intentions concerning the AI. Overall, the appraisal process is a key determinant for humans' behavioral responses (e.g., their delegation decision) and their cognitive responses (e.g., altered intentions to use the AI in the future or their attitude towards it).

A better understanding of how these appraisal processes work and how we might steer them in a specific direction to lead to the desired cognitive and behavioral responses remains an ongoing problem in IS and HCI literature. Therefore, this dissertation focuses on AI literacy as a human attribute in the sense of cognitive appraisal theory to extend our understanding of the new dynamics between humans and AI.

1.2.4 Organizational Lens: Strategic AI Orientation and Implementation Ability

Considering organizations is crucial when aiming to understand and improve human-AI collaborations since they are often the entities that decide on the adoption of AI solutions (Mikalef, Lemmer, et al., 2022; J. Yang et al., 2021). When deciding on the adoption of an AI technology, any organization should be guided by the value that the AI can provide (Jorzik et al., 2023; Shollo et al., 2022). This value is often economic value for businesses, but it could also be educational value for a school or societal value for a government organization (Mikalef, Lemmer, et al., 2022). All organizations have in common that they need to use and manage AI directed towards their purpose and not only to implement the technology for the technology's sake. AI literacy as a human trait might affect not only the humans themselves but also their organizations and could act as an enabler of value creation with AI (Hambrick & Mason, 1984).

Within an organization, the TMT is typically responsible for sustaining and enhancing the path to value creation of the respective organization (Hambrick & Mason, 1984). This path to AI adoption and subsequent value creation can be broken down into two significant steps from the perspective of the TMT: establishing strategic AI orientation (J. Li et al., 2021) and AI implementation ability (M. Weber et al., 2022). First, TMTs need to discern the potential value AI can offer and develop a strategy to harness it effectively while considering the interests of all stakeholders involved (J. Li et al., 2021). This necessitates a comprehensive understanding of AI's unique value propositions and associated risks tailored to the specific context of the firm (Shollo et al., 2022). Therefore, prior IS research conceptualized the construct of strategic AI orientation, referring to a "firm's overall strategic direction and goals associated with introducing and applying AI technology" (J. Li et al., 2021). Second, once the groundwork of strategic AI orientation is laid, TMTs pivot towards translating the identified value potentials into tangible outcomes by guiding the implementation of the developed strategy (M. Weber et al., 2022). Transitioning from strategy to implementation demands a comprehensive array of resources, encompassing IT infrastructure, intangible assets, and human capital (Roepke et al., 2000; M. Weber et al., 2022). Developing and deploying these resources determine a firm's AI implementation ability, or its "ability to implement IT systems with an AI component" (M. Weber et al., 2022).

To examine the impact of TMT AI literacy on AI orientation and AI implementation ability, this dissertation draws on upper echelons theory, which has been developed by management literature to theorize the influence of executives on their organizations (Hambrick & Mason, 1984). In general, upper echelons theory proclaims that the decisions of organizations are influenced by how their executives perceive their environment and how they pay attention (Hambrick & Mason, 1984). As such, upper echelons theory puts a strong emphasis on managerial attention and is closely tied to the attention-based view of the firm, specifying it for executives (Ocasio, 1997, 2011). Together, upper echelons theory and the attention-based view of the firm assume that the more the management focuses on a certain topic, the more resources the topic will receive, leading to the desired outcomes. According to the theory, such outcomes trace back to the decisions of executives and reflect their characteristics (Carpenter et al., 2016; Hambrick & Mason, 1984). These characteristics refer to the TMT's perceptions, skills, or expertise (Klein & Harrison, 2007) and, hence, also their AI literacy. In other words, the TMT AI literacy should direct their attention to issues such as AI adoption.

Yet, we know little about how AI's unique facets, compared to more traditional technology, affect the dynamics in organizations to adopt technology. As such, this thesis also focuses on AI literacy as an attribute of a TMT in the sense of upper echelons theory to increase our understanding of AI adoption and AI-related value creation processes, ultimately contributing to more purposeful human-AI collaborations in the organizational context.

1.3 Positioning and Structure of the Dissertation

The following section first introduces the overarching research framework of the dissertation, which positions the individual research articles (Subsection 1.3.1). Then, it lays out the structure of the dissertation, including a summary for each research article (Subsection 1.3.2). Last, it shows how this dissertation is positioned within my other AI literacy research efforts (Subsection 1.3.3).

1.3.1 Overarching Research Framework

To investigate how AI literacy can be conceptualized, measured, and enabled as well as how it affects individuals and organizations, this dissertation follows an overarching research framework (Figure 1.1) that draws on the "transfer of learning" paradigm to integrate the previously introduced theoretical perspectives and contexts (Royer, 1979; Schunk, 2012). The transfer of learning paradigm assumes that humans first acquire learnings (e.g., literacy) and that their responses to new situations are then determined by how successfully they are able to transfer such learnings to these new situations (Bobrow & Norman, 1975). Among the most prominent theories under the paradigm is schema theory, emphasizing the role of humans' inner workings over environmental influences to explain the transfer success (Royer, 1979). According to the theory, a schema refers to an abstract cognitive structure in human memory consisting of acquired experiences, information, concepts, or procedures (Royer, 1979). Whether one has specific schemata available and can activate them then determines the transfer success and subsequent response. Following prior IS studies that build on schema theory (e.g., Kang et al., 2017), AI literacy can also be viewed as a distinct human schema within this theoretical framework.

Figure 1.1 illustrates how the sequence outlined by schema theory can be applied to the AI literacy context of this dissertation (Kang et al., 2017; Royer, 1979). Initially, an individual or team acquires the cognitive schema of AI literacy through a learning experience ("Learning Leads to Literacy"). Then, outcomes of interest are determined by this schema ("Literacy Leads to Effects"), meaning the degree or existence of the schema (i.e., degree of AI literacy) affects their responses. Notably, schema theory is extended here to the organizational context in the sense that the AI literacy of a human team affects their joint responses, which then affect the organization. In summary, the framework describes how a learning experience enables AI literacy of an individual or team, which affects the response of the individual (i.e., cognition and behavior) or the team's organization (i.e., strategic AI orientation and AI implementation ability).

Building a complete understanding of AI literacy that extends our knowledge and enables us to draw concrete implications on how to improve human-AI collaboration and AI adoption requires us to understand this chain of effects holistically. To design better learning experiences for AI literacy, it is crucial to understand how the respective learnings affect the learners and materialize for them. In turn, to understand or foster specific effects of AI literacy, we need to know how to enable and measure AI literacy. To that end, Figure 1.1 shows the positioning of the three research questions of this dissertation and the respective research articles that answer them within this overarching framework.

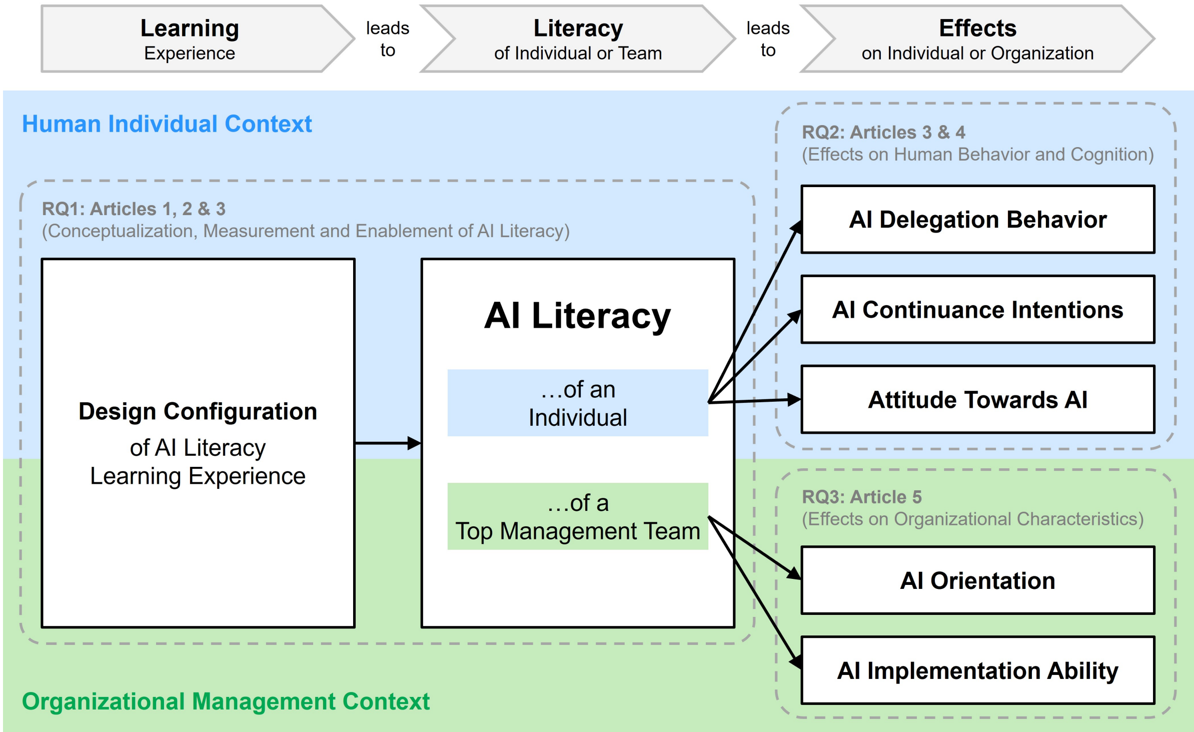

Figure 1.1: *Overarching Research Framework*

The articles concerning the first step ("Learning Leads to Literacy") draw on a systematic literature review for conceptualizing AI literacy (Article 1), a scale development methodology for establishing a measurement instrument (Article 2), and a design science project for building a learning experience (Article 3). This first step leverages theorizing for human learning motivation (i.e., self-determination theory) to inform the development. Concerning the second step ("Literacy Leads to Effects"), the articles draw on an experimental evaluation of the learning experience (Article 3), a behavioral experiment (Article 4), and an analysis of executives' skill reports, board structures, and firm reports (Article 5). This step leverages cognitive appraisal theory in the human individual context as well as upper echelons theory in the organizational management context.

1.3.2 Dissertation Structure

This dissertation consists of seven chapters. The introduction (Chapter 1) motivates the phenomenon of AI literacy and its relevance in the individual and organizational context, leading to the three research questions of this thesis. Furthermore, it introduces the theoretical foundations for the respective contexts. Chapters 2 to 6 each represent one peer-reviewed and published research article. Together, these five articles answer the three overarching research questions. Table 1.1 provides an overview of the five articles and corresponding chapters of this thesis. Chapter 7 concludes the thesis by summarizing the overarching contributions to research and theory, the implications for practice, as well as the limitations and future research.

The following provides the key conclusions together with a brief synopsis of each of the five articles, representing chapters 2 to 6 of this dissertation. The summaries and the articles themselves adopt the first-person plural perspective (i.e., we), as the articles also represent the thoughts of my co-authors who contributed to the research.

Article 1 - Chapter 2: Conceptualization

The first article contributes to answering the first overarching research question (RQ1) on how AI literacy can be conceptualized, measured, and enabled. Specifically, it is focused on answering the part of conceptualizing AI literacy for users. As laid out above, the rapid advancement of AI has brought transformative changes to various aspects of human life, leading to an exponential increase in the number of AI users (Collins et al., 2021). Users of AI can realize immense benefits through leveraging the technology but are also subject to significant new challenges. Developing AI literacy is one way for AI users to address these challenges (Long, Blunt, & Magerko, 2021). In that sense, we define AI literacy in this article as a holistic construct that refers to different human *proficiency dimensions* in different *subject areas* of AI that enable purposeful, efficient, and ethical usage of AI technologies. To understand what proficiency dimensions and what subject areas AI literacy comprises and how they can be conceptualized, the article draws on a systematic, scoping literature review. The article synthesizes the existing literature, provides a conceptual framework for organizing the research, and develops a future research agenda. Therefore, we holistically assess the fragmented AI literacy research landscape (68 papers) while critically examining its specificity to different user groups and its distinction from other technology literacies. Then, we organize our findings in an overarching conceptual AI literacy framework. As a result, the framework conceptualizes six different subject areas of AI literacy ("AI Models," "Data for AI," "AI Interfaces,"

#	Chapter and Corresponding Article
Chapter 2	**Conceptualization**
(Article 1)	Pinski, M., & Benlian, A. (2024): AI Literacy for Users – A Comprehensive Review and Future Research Directions of Learning Methods, Components, and Effects. Published in *Computers in Human Behavior: Artificial Humans. 2*(1) (VHB-Ranking[1]: -)
Chapter 3	**Measurement Development**
(Article 2)	Pinski, M., & Benlian, A. (2023): AI Literacy - Towards Measuring Human Competency in Artificial Intelligence. Published in the *Proceedings of the 56th Hawaii International Conference on System Sciences.* (VHB-Ranking: B)
Chapter 4	**Enablement Development and Effects on Human Cognition**
(Article 3)	Pinski, M., Haas, M., & Franz, A. (2023): AiLingo – A Design Science Approach to Advancing Non-Expert Adults' AI Literacy. Published in the *Proceedings of the Forty-Fourth International Conference on Information Systems.* (VHB-Ranking: A) Awarded as Best Design Science Paper Runner Up
Chapter 5	**Effects on Human Behavior**
(Article 4)	Pinski, M., Adam, M., & Benlian, A. (2023): AI Knowledge: Improving AI Delegation through Human Enablement. Published in the *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23).* (VHB-Ranking: A)
Chapter 6	**Effects on Organizational Characteristics**
(Article 5)	Pinski, M., Hofmann, T., & Benlian, A. (2024): AI Literacy for the Top Management: An Upper Echelons Perspective on Corporate AI Orientation and Implementation Ability. Published in *Electronic Markets. 34*(1) (VHB-Ranking: B)

1. 2024 ranking from "Verband der Hochschullehrerinnen und Hochschullehrer für Betriebswirtschaft"

Table 1.1: *Overview of Articles Included in the Dissertation*

"AI Tools," "Humans, Organizations, and Society," and one "Cross Area") as well as five proficiency dimensions ("Knowledge," "Awareness," "Skills," "Competencies," and "Experience"). For each component of each subject area, it discerns its specificity to AI based on three AI facets (Berente et al., 2021). Moreover, the article identifies and structures the learning methods leading to and the effects stemming from AI literacy. Last, the article provides a research agenda - oriented along the developed conceptual framework – shedding light on the most promising research opportunities based on the assessment of the existing literature.

Article 2 - Chapter 3: Measurement Development

The second article also aims to answer the first overarching research question (RQ1). It particularly focuses on the part of how to measure AI literacy. While past studies have identified many effects of AI technology on human-AI collaborations (Jarrahi, 2018), there is a paucity in the literature regarding the human factors that affect this relationship. Only little research has been conducted on how to measure these (e.g., B. Wang et al., 2022). Therefore, the second article sets out to develop a measurement instrument (scale) for the AI literacy of individuals. It follows established scale development procedures (MacKenzie et al., 2011). As such, we conducted a systematic literature review followed by five expert interviews to define the focal measurement construct of (general) AI literacy and to generate an initial set of items. Furthermore, we performed two rounds of card sorting with six and five judges and a pre-test study with 50 participants to evaluate the developed scale. The validated measurement instrument contains five dimensions and 13 items. The article provides empirical support for the measurement model and concludes with future research directions.

Article 3 - Chapter 4: Enablement Development and Effects on Human Cognition

The third article draws on a design science research approach to develop an AI literacy learning experience in the form of a mobile learning application called “AiLingo.” The article has two research goals. It answers the last part of the first research question (RQ1) by designing an AI literacy learning experience that sheds light on how to enable AI literacy. Moreover, it evaluates the designed AI literacy learning experience to investigate how AI literacy materializes in different aspects of human cognition (i.e., AI-related intentions and attitudes). Thus, the experimental evaluation of this design artifact aims to answer the second research question (RQ2), specifically the effects of AI literacy on human cognition. While IS research on AI education has primarily focused on students in formal learning settings (Druga & Ko, 2021; Steinbauer et al., 2021), it mostly neglected non-expert adults and informal learning settings. The article focuses on non-experts who particularly struggle in human-AI collaboration due to their unfamiliarity with the unique AI facets, such as inscrutability (Berente et al., 2021; Maitz et al., 2022). As an informal

AI literacy learning experience, AiLingo is developed to advance non-expert adults' AI literacy in several game-like lessons. Building on self-determination theory, the article deducts three design principles tailored to non-expert adults ("Intuitive AI function understanding," "Interactive, non-expert-friendly elements," and "Real-life relatable AI examples"), which are instantiated as three design features ("AI functioning visualization," "Open-ended, high-level AI model configuration," and "Non-expert relatable AI use cases"). Thereafter, it evaluates the instantiated features in an experiment (n = 101). Concerning the overarching RQ1, we find that a learning experience where our design features are present (vs. absent) leads to greater AI literacy advancement. Concerning the overarching RQ2, we find that AI literacy advancement increases AI usage continuance intention and leads to a more positive attitude toward AI.

Article 4 - Chapter 5: Effects on Human Behavior

The fourth article continues with the investigation of the second research question (RQ2), focusing on the effects of AI literacy on human behavior. The study is motivated by the tension that human-AI collaborations increasingly require humans to delegate to AI, even though humans are often ineffective at delegating (Lai et al., 2022). Humans and AI can have complementary competencies that would enable superior performance on certain tasks (Fügener et al., 2021a), yet humans fail at making the right delegation decisions. The article introduces AI literacy as a potential enabler for more appropriate delegation in human-AI collaborations. Therefore, we conducted a between-subjects experiment (two groups, n = 111) to examine how enabling humans with AI literacy (in this experiment, specifically the knowledge part of AI literacy) can improve AI delegation in human-AI collaboration. We find that humans who received an AI literacy training align their delegation decisions more closely with their assessment of how suitable a task is for humans compared to AI (i.e., task appraisal). We show that the alignment of one's delegation decisions and task appraisal increases task performance. Moreover, we discuss the article's findings concerning their implications for HCI design guidelines. For example, one could consider AI features that educate humans regarding the general functioning of AI and their own (human) performance and biases.

Article 5 - Chapter 6: Effects on Organizational Characteristics

The fifth article addresses the third research question (RQ3), asking how the AI literacy of a TMT affects their organization's AI orientation as well as AI implementation ability.

Since the article shifts the context from the individual to the organization, it draws on upper echelons theory, which theorizes that outcomes in organizations are determined by the characteristics of the organization's executives (Hambrick, 2007; Hambrick & Mason, 1984). AI orientation and AI implementation ability are both paramount for value generation with AI (J. Li et al., 2021; M. Weber et al., 2022). Whereas a firm's AI orientation enables it to identify AI value potentials, AI implementation ability empowers it to realize these value potentials. Moreover, the article builds on the notion that the effects of TMTs are dependent upon the context of the firm (Hambrick, 2007). Therefore, it considers the moderating influence of a firm's type (i.e., startups vs. incumbents). To investigate the relationships between TMT AI literacy, AI orientation, AI implementation ability, and firm type, we use observational literacy data from 6,986 executives from a professional social network (LinkedIn.com) and firm data from 10-k statements. We find that TMT AI literacy positively affects AI orientation as well as 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. Overall, the article shows that the AI literacy of executive teams impacts organizations beyond their strategy, while the strength of this influence depends on the characteristics of the firm context.

1.3.3 Positioning within AI Literacy Research Program

During my time as a doctoral candidate, I pursued the topic of AI literacy in the form of a broad research program. I published or submitted for publication several other research articles that are not part of this dissertation. Figure 1.2 provides an overview of how my other articles concerning AI literacy relate to the contents of this dissertation. Together, they represent all my efforts – during my time as a doctoral candidate – to extend our knowledge of AI literacy.

Further articles published (not part of this dissertation):

- Pinski, M., Haas, M. and Benlian, A. (2024). Building Metaknowledge in AI Literacy – The Effect of Gamified vs. Text-based Learning on AI Literacy Metaknowledge. *Proceedings of the 57th Hawaii International Conference on System Sciences*. https://hdl.handle.net/10125/107004 (VHB-Ranking: B)
- Pinski, M., Hofmann, T., and Benlian, A. (2023). Executive AI Literacy: A Text-Mining Approach to Understand Existing and Demanded AI Skills

of Leaders in Unicorn Firms. *Proceedings of the Wirtschaftsinformatik 2023.* https://aisel.aisnet.org/wi2023/7 (VHB-Ranking: B, Nominated for Best Paper Award)

- Pinski, M., Tarafdar, M., and Benlian, A. (2024). Why Executives Can't Get Comfortable with AI - AI will require continuous learning: Leaders need to embrace that uncomfortable reality and prioritize developing AI literacy. *MIT Sloan Management Review.* https://sloanreview.mit.edu/article/why-executives-cant-get-comfortable-with-ai/#article-authors (VHB-Ranking: B)

- Knoth, N., Decker, M., Laupichler, M., Pinski, M., Buchholtz, N., Bata, K., Schultz, B. (2024). Developing a Holistic AI Literacy Assessment Matrix - Bridging Generic, Domain-Specific, and Ethical Competencies. *Computers and Education Open.* https://doi.org/10.1016/j.caeo.2024.100177

- Weber, P., Baum, L. and Pinski, M. (2023). Messung von AI Literacy – Empirische Evidenz und Implikationen. *Proceedings of the Wirtschaftsinformatik 2023.* https://aisel.aisnet.org/wi2023/3 (VHB-Ranking: B)

- Weber, P., Pinski, M. and Baum, L. (2023). Toward an Objective Measurement of AI Literacy. *Proceedings of the Pacific Asia Conference on Information Systems.* https://aisel.aisnet.org/pacis2023/60 (VHB-Ranking: C)

Further articles submitted for publication (not part of this dissertation):

- Pinski, M., Weber, P., Baum, L., Hinz, O., and Benlian, A. Effects of AI Literacy and Domain Knowledge on Human-AI Task Performance. *Manuscript submitted to Journal of the Association for Information Systems.* (VHB-Ranking: A)

- Benlian, A., Adam, M., Pinski, M. Team-Enacted Use Versus Developer-Needed Use of Agile Practices: How (In-)Congruence and an Agile Mindset Shape Developer Well-Being. *First revision submitted to Information Systems Research.* (VHB-Ranking: A+)

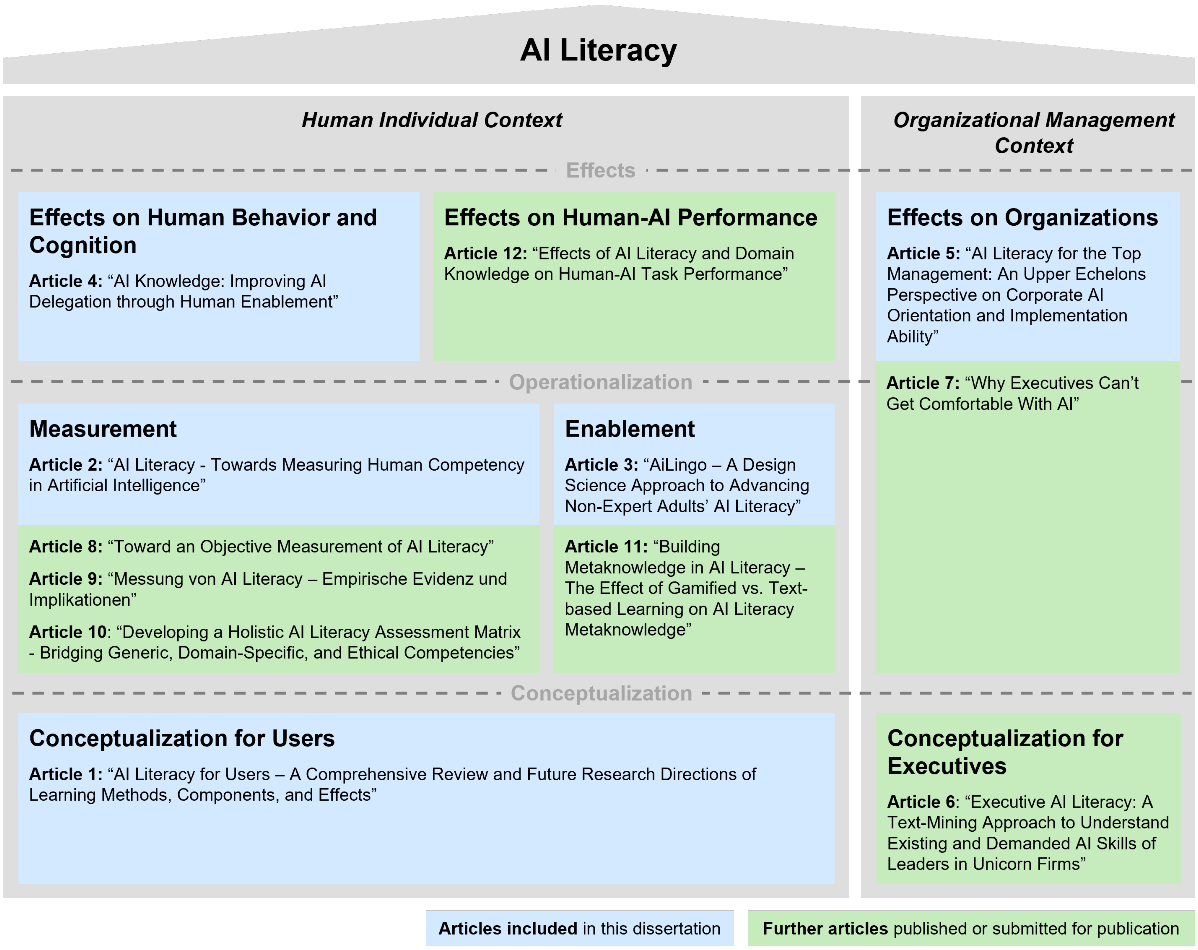

Figure 1.2: *AI Literacy Research Program*

2 Conceptualization

Title:	AI Literacy for Users – A Comprehensive Review and Future Research Directions of Learning Methods, Components, and Effects
Authors:	Marc Pinski, Technische Universität Darmstadt, Germany Alexander Benlian, Technische Universität Darmstadt, Germany
Published in:	Computers in Human Behavior: Artificial Humans. 2(1)
Available at:	www.doi.org/10.1016/j.chbah.2024.100062

Abstract

The rapid advancement of artificial intelligence (AI) has brought transformative changes to various aspects of human life, leading to an exponential increase in the number of AI users. The broad access and usage of AI enable immense benefits but also give rise to significant challenges. One way for AI users to address these challenges is to develop AI literacy, referring to human proficiency in different subject areas of AI that enable purposeful, efficient, and ethical usage of AI technologies. This study aims to comprehensively understand and structure the research on AI literacy for AI users through a systematic, scoping literature review. Therefore, we synthesize the literature, provide a conceptual framework, and develop a research agenda. Our review paper holistically assesses the fragmented AI literacy research landscape (68 papers) while critically examining its specificity to different user groups and its distinction from other technology literacies, exposing that research efforts are partly not well integrated. We organize our findings in an overarching conceptual framework structured along the learning methods leading to, the components constituting, and the effects stemming from AI literacy. Our research agenda - oriented along the developed conceptual framework – sheds light on the most promising research opportunities to prepare AI users for an AI-powered future of work and society.

Keywords: Systematic Literature Review, Scoping Literature Review, Artificial Intelligence Literacy, Learning Methods, AI Literacy Components, AI Literacy Effects

2.1 Introduction

"Building an AI-powered society that benefits all requires each of us to become literate about AI."
World Economic Forum (2022b) in "Without universal AI literacy, AI will fail us"

In the past decade, the rapid advancement of artificial intelligence (AI) has brought transformative changes to how humans work, interact, and live – thereby significantly increasing the number of AI users (Jain et al., 2021). The AI-powered large language model ChatGPT released in November 2022, based on the novel generative pre-trained transformer (GPT) technology, broke the all-time record in technology adoption speed with 100 million users in only two months (Milmo, 2023). However, AI's transformative changes come with challenges unseen by users, such as, in the GPT-based AI context, phenomena like "hallucinations," describing incorrect output appearing logical and cohesive at first sight (Brynjolfsson et al., 2023; B. Peng et al., 2023). Research and practice are eager to develop technological solutions to address these challenges, such as large language models warning users about potential hallucinations (Ortiz, 2023). Still, technological features alone do not ensure successful human-AI collaboration. Human-centered approaches are necessary to complement the technology itself (Marcolin et al., 2000; Torkzadeh & Koufteros, 1993). Researchers from various disciplines at the intersection of humans and technology, such as human-computer interaction (HCI; e.g., Long and Magerko, 2020), computer education (CED; e.g., Ng et al., 2021), or information systems (IS; e.g., Heyder and Posegga, 2021), have recently coined the concept of AI literacy as such a human-centered approach. Whereas multiple AI literacy definitions exist, all refer to some dimension of human proficiency (e.g., knowledge, skills, competencies) regarding different subject areas of AI (e.g., AI models, ethical implications, knowledge representations) that enable purposeful usage of AI or interaction with AI (e.g., Hermann, 2021; Kandlhofer et al., 2016; Long and Magerko, 2020). For example, AI literacy empowers AI users to understand the fundamental principles of AI, enabling them to recognize potential biases and understand the ethical considerations involved (B. Wang et al., 2022).

While AI in the form of large language models received much attention recently, the new challenges for AI users extend to all AI-based technologies, which can be characterized by three distinguishing facets: learning ability, increased autonomy, and inscrutability (Berente et al., 2021). Technology with these characteristics (i.e., AI tools) has become pervasive. At the same time, AI users have mostly been left ill-prepared to comprehend, utilize, and critically engage with AI – that is, they have been left AI illiterate at large (Maitz et al., 2022; Wilton et al., 2022). This mismatch raises concerns not only about the efficiency and effectiveness of human-AI collaborations but also about privacy, ethics, and bias (Mikalef, Conboy, et al., 2022). Hence, developing a comprehensive understanding of AI literacy is crucial to preparing AI users for an AI-powered future of work and society.

Prior AI literacy research in the emerging literature stream started to build our understanding of AI literacy along three research avenues that can be seen as three logically consecutive steps: The *learning methods* leading to AI literacy (e.g., Long, Blunt, and Magerko, 2021), the *components* constituting AI literacy (e.g., Ng et al., 2021), and the *effects* resulting from AI literacy (e.g., Pinski, Adam, and Benlian, 2023). Each step is highly relevant for a comprehensive understanding of AI literacy. First, since AI technologies are evolving rapidly, it is essential to understand the most effective *learning methods* for equipping different AI users with the needed AI literacy. Understanding how AI users can best grasp novel AI concepts relevant to them enables the development of targeted educational initiatives. Therefore, building a broad repertoire of formal and informal learning methods tailored to conveying AI literacy is necessary (Long, Blunt, & Magerko, 2021). Second, much prior research focused on conceptualizing different AI literacy *components*, for example, individual AI skills or knowledge concerning different AI subjects (e.g., Long and Magerko, 2020; Ng et al., 2021). As different AI user groups have different AI literacy requirements, it is vital to understand and build a repository of AI literacy components and their relevancy to different AI user groups. For example, a manager (Jorzik et al., 2023) needs different AI skills and knowledge than a teacher (Kim & Kwon, 2023). Third, it is important to understand if AI literacy results in the intended *effects*. For instance, previous research has shown that AI literacy can positively affect the performance of human-AI collaboration while simultaneously reducing humans' intention to use AI in the future (Pinski, Adam, & Benlian, 2023). Given that AI might affect humans differently compared to what we have learned with non-AI technology, it is imperative to better understand the diverse effects of AI literacy to foster desired effects and prevent unwanted effects.

While research has accumulated within these three research avenues, the overall AI literacy research landscape remains fragmented, with many questions unanswered (Pinski, Adam, & Benlian, 2023). Therefore, we need a comprehensive assessment of the recent scientific discourse that systemizes existing knowledge and guides future research. Prior reviews focused on one particular research avenue, identifying several relevant AI literacy components (e.g., Long and Magerko, 2020; Ng et al., 2021). Other studies focused on a particular proficiency dimension or selected subject areas within the research avenue of AI literacy components (Carolus, Augustin, et al., 2023; Laupichler, Aster, Haverkamp, & Raupach, 2023). However, the field has matured significantly in the past three years, and research has also been conducted in the other two avenues (learning methods and effects) (e.g., Chiang and Yin, 2022; Long, Blunt, and Magerko, 2021; Pinski, Adam, and Benlian, 2023).

Furthermore, as AI users are growing in number across and within domains, it becomes apparent that there is no one AI literacy solution for all different AI user groups (Benlian, 2022; Meske et al., 2020). There is a notion in the AI literacy literature to distinguish expert users, predominantly from the organizational context, and non-expert users, predominantly from the personal context, like humans using their smartphones (Laupichler, Aster, Haverkamp, & Raupach, 2023; Pinski, Haas, & Franz, 2023). These two broad user group categories comprise different, more specific individual AI user groups, for example, managers, teachers, and medical doctors within the expert category. As of now, we lack oversight of which individual AI user groups the literature has covered so far.

In addition, many studies assume an implicit understanding of AI, making it difficult to distinguish AI literacy from other technology literacies, like digital literacy. As a research community, we need to be specific about AI literacy. To our knowledge, no prior work has scrutinized the AI literacy literature regarding its AI-specificity using a well-grounded AI understanding, such as the introduced AI facets of Berente et al. (2021): autonomy, inscrutability, and learning.

This study aims to assess the scope of the fragmented research landscape in each of the introduced AI literacy research avenues and organize the research into a conceptual framework by answering the following research questions. Furthermore, it aims to assess the scope of AI user groups covered by the literature and scrutinize what we understand under the construct of AI literacy by leveraging established facets of AI (Berente et al., 2021):

> *RQ1: Which learning methods have been identified leading to AI literacy for AI users?*
>
> *RQ2: Which components have been identified as constituting AI literacy for AI users?*

RQ3: Which effects have been identified that AI literacy has on AI users?

We attempt to answer these research questions using a systematic, scoping literature review approach (Paré et al., 2015). Particularly in emerging research fields such as AI literacy, a (scoping) literature review can help to establish "a firm foundation for advancing knowledge" (Webster & Watson, 2002, p. 13). With this scoping literature review, we make the following contributions:

(1) While prior research focused on particular aspects of AI literacy (e.g., Long and Magerko, 2020 for components), our review extends this by developing an overarching conceptual framework comprising detailed conceptualizations for each AI literacy aspect (learning methods, components, and effects). To our knowledge, no reviews regarding learning methods and the effects of AI literacy have been conducted. Our scoping review extends the conceptual understanding of AI literacy by structuring the currently fragmented discourse.

(2) Drawing from our comprehensive conceptual framework, we outline a research agenda that identifies the key areas of opportunity for scholars in the field of AI literacy. We outline different future research directions for the learning methods, components, and effects of AI literacy.

(3) Prior studies either have not accounted for AI user group differences or have focused on individual AI user groups (e.g., Charow et al., 2021). This review contributes a holistic analysis of AI user groups discussed within both the expert and non-expert domains, shifting the discourse to consider AI user group differences more thoroughly. Further, the holistic user group analysis uncovers yet unexplored AI user groups.

(4) Much prior research investigated highly relevant aspects of AI literacy while leaving it unclear how the AI literacy construct is distinct from prior technology literacies, such as digital or data literacy. Our review departs from this by assessing the AI-specificity of the components (e.g., different skills and knowledge) ascribed to AI literacy by the literature. Therefore, we use three AI facets from an established AI definition (Berente et al., 2021): autonomy, inscrutability, and learning. We use the facets for a structured distinction of AI from non-AI technology, enabling us to distinguish AI literacy from other technology literacies. By applying this AI lens, we contribute to a more thorough understanding of what AI literacy refers to and how the construct relates to other literacies.

(5) Concerning practice, this review also provides a reference for educators, policymakers, and business decision-makers who make crucial decisions concerning the standards of AI literacy in educational institutions, society, and business.

2.2 Conceptual Background

2.2.1 Artificial Intelligence

While the concept of AI was first mentioned in the 1950s (McCarthy et al., 1955; Turing, 1950), attention to the topic fluctuated over the years, including periods with very little attention known as AI winters (Hendler, 2008). In recent years, increased computing capacity and major technological breakthroughs like the transformer technology (Vaswani et al., 2017) enabled new AI technologies, such as large language models (Brynjolfsson et al., 2023), which led to massive attention paid to the topic not only by the academic and business communities but also by large (non-expert) parts of society (Q. N. Nguyen et al., 2022). Nevertheless, AI remains a diffuse concept, and manifold definitions exist even within research fields (Collins et al., 2021). For example, Rai et al. (2019, p. iii) see AI as the "ability of a machine to perform cognitive functions that we associate with human minds [...]," whereas Duan et al. (2019, p. 1) refer to AI as "the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks."

However, when aiming to conceptualize AI literacy and delineate it from related concepts, such as digital or data literacy, it is purposeful to use criteria that enable a distinction between AI technologies and non-AI technologies. Most AI definitions have a reference to humans and human skills in common (Collins et al., 2021). Berente et al. (2021, p. 1435) make this explicit in their AI definition, viewing AI as "the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems." Building on their definition, they provide three facets of AI technologies that one can use as a framework to assess AI-specificity: autonomy, learning, and inscrutability.

AI technologies are increasingly more *autonomous*, as they can act without human intervention (Baird & Maruping, 2021). The autonomous decisions of these technologies have tangible effects, often without humans being aware that these decisions have been made by an AI technology (Murray et al., 2021). Examples include self-driving vehicles (Fernandez Domingos et al., 2022), robo-advisors for investments (I. Lee & Shin, 2018), and AI underwriters for loans (Markus, 2017). *Learning* is fundamental to AI, with data and experience enabling automatic improvement (Turing, 1950). Recent breakthroughs in big data (Chen et al., 2012) have led to advancements in deep and reinforcement learning (Janiesch et al., 2021), allowing AI to handle complex decision-making involving complex audio, text, and object recognition as well as generative capacities (Brynjolfsson et al., 2023). *Inscrutability* accompanies AI's progress, generating algorithmic models and outputs that are intelligible only to select audiences or sometimes remain opaque to all humans (Arrieta et al., 2020). Rising computing capacities allowed developers to construct AI technologies, such as neural networks, based on so many intertwined parameters that decision-making is often incomprehensible to the human mind (Brasse et al., 2023).

2.2.2 Prior Technology Literacies

Literacy is not a static concept but is under constant evolution based on the technological and social developments of society (Leu et al., 2013). Literacy in the technology context has evolved significantly beyond its traditional definition of being able to read and write (Leu et al., 2004). The broader literacy notion now encompasses specialized literacies tailored to specific technological domains, such as digital, data, and media literacy (Eshet-Alkalai, 2004; Potter, 2013; Wolff et al., 2016), which are, however, continuously evolving (Leu et al., 2013). While each literacy concept evades an agreed-upon definition in the literature, scholars have identified common themes of the literacy construct within each discourse (Eshet-Alkalai, 2004; Potter, 2013; Wolff et al., 2016).

Digital literacy is among the most prominent technology literacy concepts (Gilster, 1997; Neumann et al., 2016; Njenga, 2018). Eshet-Alkalai (2004, p. 1) characterizes digital literacy as comprising a "large variety of complex cognitive, motor, sociological, and emotional skills, which users need in order to function effectively in digital environments." However, the literature goes beyond viewing digital literacy merely as a skill-based construct. Research also emphasizes that digital literacy should empower humans "to appropriately respond, in socially recognised ways, to even future challenges through sharing and creating knowledge and eventually participating in the society" (Njenga, 2018, p. 2). This holistic perspective elevates digital literacy beyond a mere set of skills by setting the technology it relates to in the social context (Feerrar, 2019). One can find similar themes of defining "literacy" holistically in other literacy concepts (Livingstone, 2004). When conceptualizing media literacy, Potter (2004) argues that the literacy concept encompasses knowledge and skills in different domains as well as "personal locus," which refers to emotional commitment and drive to search for information and experiences to attain your goals. Regarding data literacy, on the one hand, research mentions that it encompasses knowledge and skill components, such as data analysis techniques (Kerpedzhiev et al., 2020). On the other hand, the literature also emphasizes that data literacy contains ethical and critical judgment (Someh et al., 2019) and an understanding of how data literacy impacts society (Wolff et al., 2016).

Taken together, the different literacies share common elements that transcend their specific domains. They all emphasize holistic proficiency, which means going beyond merely accumulating knowledge or skills. Through knowledge and skill, technology literacies should enable efficient and effective usage. Individuals must be able to use technology productively, maximizing its potential benefits. Beyond that, technology literacies must connect the technology to its social context, which means ethical, responsible, and critical interaction. Ethical considerations and responsible behavior are integral to these literacy concepts, ensuring individuals engage with technology morally and conscientiously. This view is underlined by the (World Economic Forum, 2018, 2020), contending that everyday life and employment skills have shifted from technology-centered skills to a broader set, including analytical thinking, active self-driven learning, and (global) citizenship. In summary, technological literacies can be described as holistic constructs of human proficiency, including reflection and deliberation, that enable humans to use technology purposefully, efficiently, and ethically (Deuze & Beckett, 2022).

2.2.3 The Need for AI Literacy

AI's specific facets (autonomy, learning, and inscrutability) caused the invalidation of multiple core assumptions fundamental to human-technology interaction held for decades (Berente et al., 2021; Schuetz & Venkatesh, 2020). For example, AI technologies break the assumption of functional consistency because they can learn from processed data, thus behaving differently over time. Furthermore, they remove the necessity of an artificial interface through more natural interactions like speech, thus enabling the possibility that humans might not be aware of their interactions with AI technologies, such as with voice assistants like Alexa or chatbots (Schuetz & Venkatesh, 2020). This invalidation of human-technology interaction assumptions, in combination with the increasingly widespread implementation of AI in the broader work-related and societal context (Berente et al., 2021), makes the need for a revised technology literacy concept apparent, i.e., AI literacy. Furthermore, the ethical challenges of AI are looming larger than before due to the increasingly human-like and beyond-human capacities (e.g., due to deep-fakes). In other words, AI literacy is necessary for the broader user base to comprehend and respond to this human-technology interaction paradigm shift.

Similar to prior literacy concepts, different definitions of AI literacy for AI users exist in the literature (see Table 2.1). One can observe that these definitions also emphasize holistic proficiency regarding different subject areas of AI. As part of AI literacy, scholars mention AI competencies (e.g., Carolus, Augustin, et al., 2023; Long and Magerko, 2020), AI abilities (e.g., Laupichler et al., 2022), or AI knowledge and understanding (e.g., Dai et al., 2020; Hermann, 2021). Together, this holistic proficiency should create an understanding of AI, enable self-determined, effective, and ethical interaction with AI, empower to utilize AI actively (in the workplace and everyday life), and allow to critically evaluate AI (Carolus, Augustin, et al., 2023; Cetindamar et al., 2022; Dai et al., 2020; Hermann, 2021; Kong et al., 2021; Laupichler et al., 2022; Long and Magerko, 2020; Ng et al., 2022).

Moreover, the different AI literacy definitions show which AI users the literature refers to (see Table 2.1). On a fundamental level, researchers distinguish between AI users as non-experts predominantly in their personal roles as citizens of society or for their personal usage of AI (e.g., Carolus, Koch, et al., 2023; Laupichler et al., 2022) and AI users as experts predominantly in their organizational roles in a work-related context (e.g., Cetindamar et al., 2022; Long and Magerko, 2020). The AI literacy requirements of different AI user groups are conceivably specific to the respective AI user group based on their usage of AI.

Following the tradition of technological literacies, we view AI literacy as a construct comprising multiple proficiency dimensions as expressed by the different definitions in the literature (see Figure 2.1 and Table 2.1). These proficiency dimensions relate to different AI subject areas and have together primarily an enabling character for efficient, self-determined, and critical usage of technology that is autonomous, can learn, or is inscrutable. By defining AI literacy as an enabling construct, we view it as distinct from mere attitudes towards AI (Schepman & Rodway, 2022), trust in AI (Kaplan et al., 2023), or the intention to use AI (Pinski, Adam, & Benlian, 2023). While all these constructs might be related to AI literacy, they express, for example, humans' affective characteristics rather than an enabling, holistic proficiency.

Source	AI User Domain	Definition
Carolus, Augustin, et al. (2023, p. 1)	Non-expert	AI literacy covers "competencies needed to interact with AI technology in a self-determined and rational manner."
Cetindamar et al. (2022, p. 11)	Expert	Employees' AI literacy is "a collection of technology, work, human-machine, and learning capabilities. These capabilities could allow employees to actively join in on designing and utilizing AI at their workplaces."
Dai et al. (2020, p. 3)	Non-expert	Student's AI literacy is the "ability to access and use AI-related knowledge and skills."
Deuze and Beckett (2022, p. 1)	Expert	AI literacy is "the knowledge and beliefs about artificial intelligence which aid their recognition, management, and application."
Hermann (2021, p. 1270)	Non-expert	AI literacy is an "individuals' basic understanding of (a) how and which data are gathered; (b) the way data are combined or compared to draw inferences, create, and disseminate content; c) the own capacity to decide, act, and object; (d) AI's susceptibility to biases and selectivity; and (e) AI's potential impact in the aggregate."
Laupichler et al. (2022, p. 1)	Non-expert	AI literacy is "the ability to understand, use, monitor, and critically reflect on AI applications without necessarily being able to develop AI models themselves."
Kong et al. (2021, p. 2)	Non-expert	AI literacy "includes three components: AI concepts, using AI concepts for evaluation, and using AI concepts for understanding the real world through problem solving."
Long and Magerko (2020, p. 2)	Expert & Non-expert	AI literacy is "a set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace."
Ng et al. (2022, p. 1)	Non-expert	A I literacy is "a new set of technological attitudes, abilities and competencies that people use AI effectively and ethically in everyday life."
Pinski and Benlian (2023, p. 169)	Expert & Non-expert	"General AI literacy is humans' socio-technical competence consisting of knowledge regarding human and AI actors in human-AI interaction, knowledge of the AI process steps, that is input, processing, and output, and experience in AI interaction."

Table 2.1: *AI Literacy Definitions (in alphabetical order)*

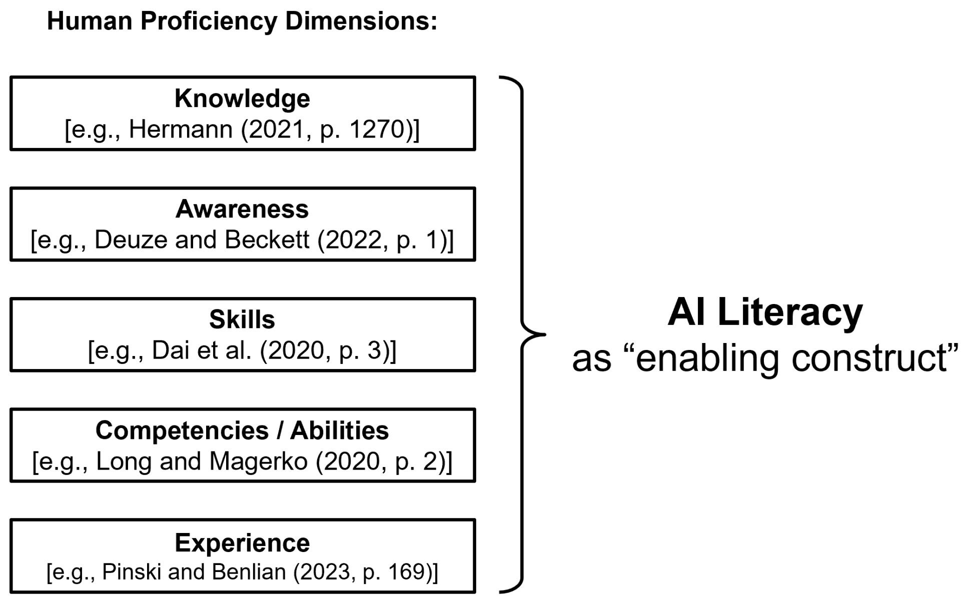

Figure 2.1: *AI Literacy Proficiency Dimensions*

2.3 Method

To answer our research questions on AI literacy, we conducted a scoping literature review, adhering to the established methodology within the family of systematic literature reviews (Kitchenham & Charters, 2007; Paré et al., 2015; Schryen et al., 2021; Webster & Watson, 2002). A scoping literature review is characterized by a comprehensive search strategy aimed at covering the breadth of the literature, an explicit study selection to eliminate studies that do not address the research questions, and a content analysis, which is topic-centric rather than author-centric (Paré et al., 2015). Furthermore, by employing this approach, we aim to develop a conceptual framework that organizes the AI literacy literature overall and more detailed "deep-dives" for individual aspects of the framework where appropriate. We selected the corpus of literature for analysis by following a five-step search and selection process (see Figure 2.2). Details on the coding process are available in Appendix 2.A.

2.3.1 Search Process

In the first step, we conducted an initial search to systematically identify relevant papers using the following search parameters. We used the broad search string "AI literacy" OR "artificial intelligence literacy" to ensure we captured all relevant articles. By including "literacy" in the search terms, we deliberately aimed to focus on articles that refer specifically to the broader, more holistic concept. We queried the key academic databases for HCI and IS research (ACM, AIS, Emerald, IEEE, Informs, JSTOR, Science Direct, Taylor & Francis, and Web of Science). We did not apply any date filters. The initial search resulted in 341 articles.

2.3.2 Selection Process

To select the relevant articles, we first excluded articles based on three technical exclusion criteria: non-English, duplicate, and non-peer-reviewed / non-scientific articles. As a result, 56 articles were excluded at this stage. Then, two independent coders conducted an abstract screening of all 285 remaining articles. Discrepancies in the coding were discussed individually until the coders achieved consensus. The exclusion criteria at this stage were that the papers were either not AI-literacy-focused, for example, when only mentioning the term to motivate a different topic, or not user-focused, such as developer-focused papers. As such, we ensured that we only included articles related to this review's defined scope. In the fourth step, we read all identified papers fully and applied the same exclusion criteria as in the third step. As a result, 52 papers remained in the selection. Finally, we conducted a forward and backward search of the identified articles, adding 16 papers to the selection, which totals 68 papers included in the final selection. By implementing this rigorous search and screening strategy, we aimed to compile a comprehensive collection of scholarly articles that meet the specific requirements of this study on AI literacy.

2.4 Results

In the following, we report the results of our literature review. Descriptive literature metrics (e.g., publication year, discipline, applied methodologies) of the compiled corpus are available in Appendix 2.B. We developed an overarching conceptual framework of AI literacy (Figure 2.3), which corresponds to the three main avenues of AI literacy research, as well as our two analytical lenses – specificities implied either due to the distinguishing facets of AI or due to the different user groups of AI. The three main avenues of AI literacy research (learning methods, components, and effects) follow a logical order, such that the learning methods enable humans to acquire AI literacy, the components describe what the acquired AI literacy consists of, which then results in the effects for the humans in question. All three are affected by the specific facets

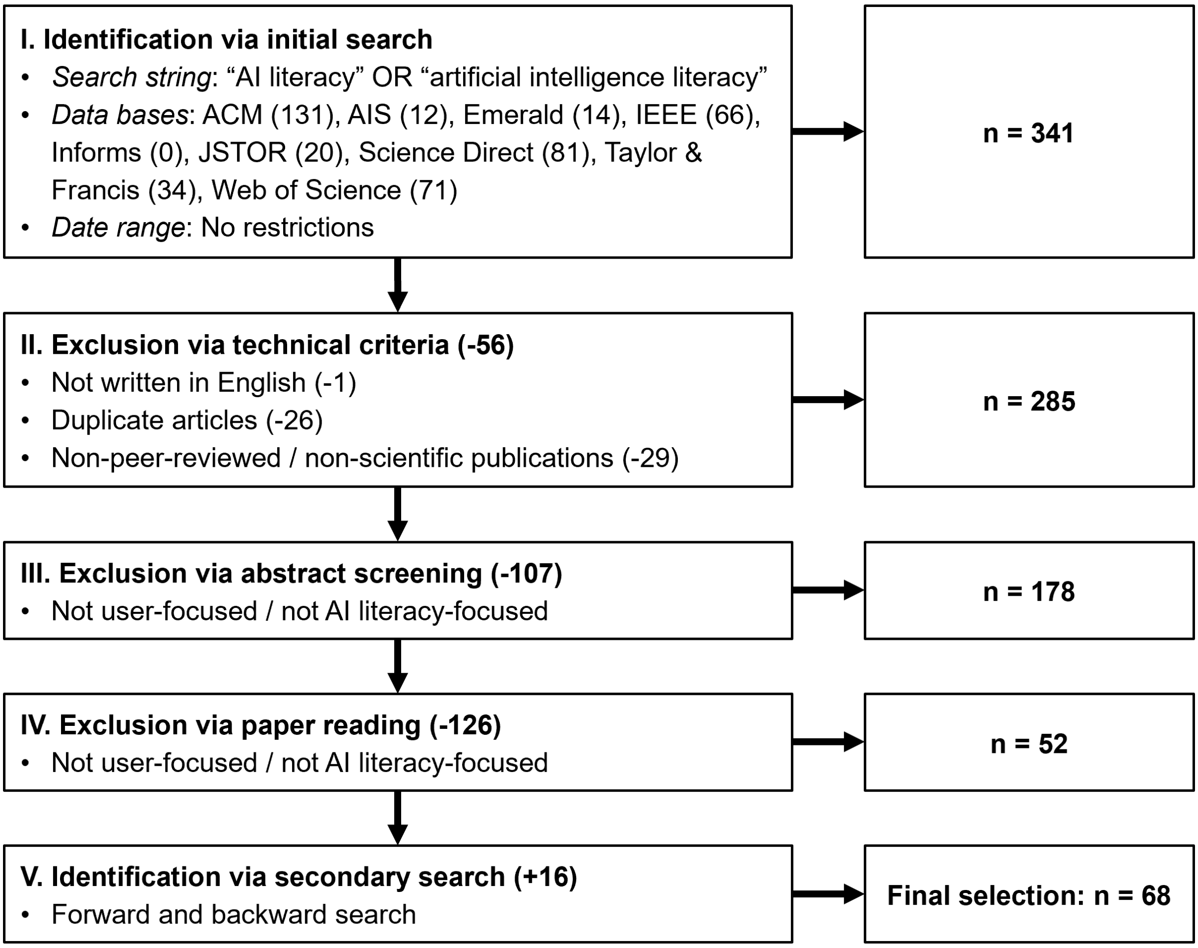

Figure 2.2: *Search and Selection Process*

of AI (Berente et al., 2021) and the user group one belongs to. Before reviewing the results of each of the three AI literacy avenues, we will report our results regarding the different types of AI users found in the literature (Subsection 2.4.1). Then, we review the learning methods (Subsection 2.4.2), AI literacy components (Subsection 2.4.3), and effects (Subsection 2.4.4).

2.4.1 AI Users

Since we focus on AI literacy for AI users, we must distinguish and comprehensively understand the AI user groups discussed in the existing literature. To achieve this, we examined the identified AI literacy literature corpus and other literature structuring the discourse on AI usage (Jain et al., 2021). AI users can be set apart from AI developers based on their interaction type with AI technology, that is, the usage of

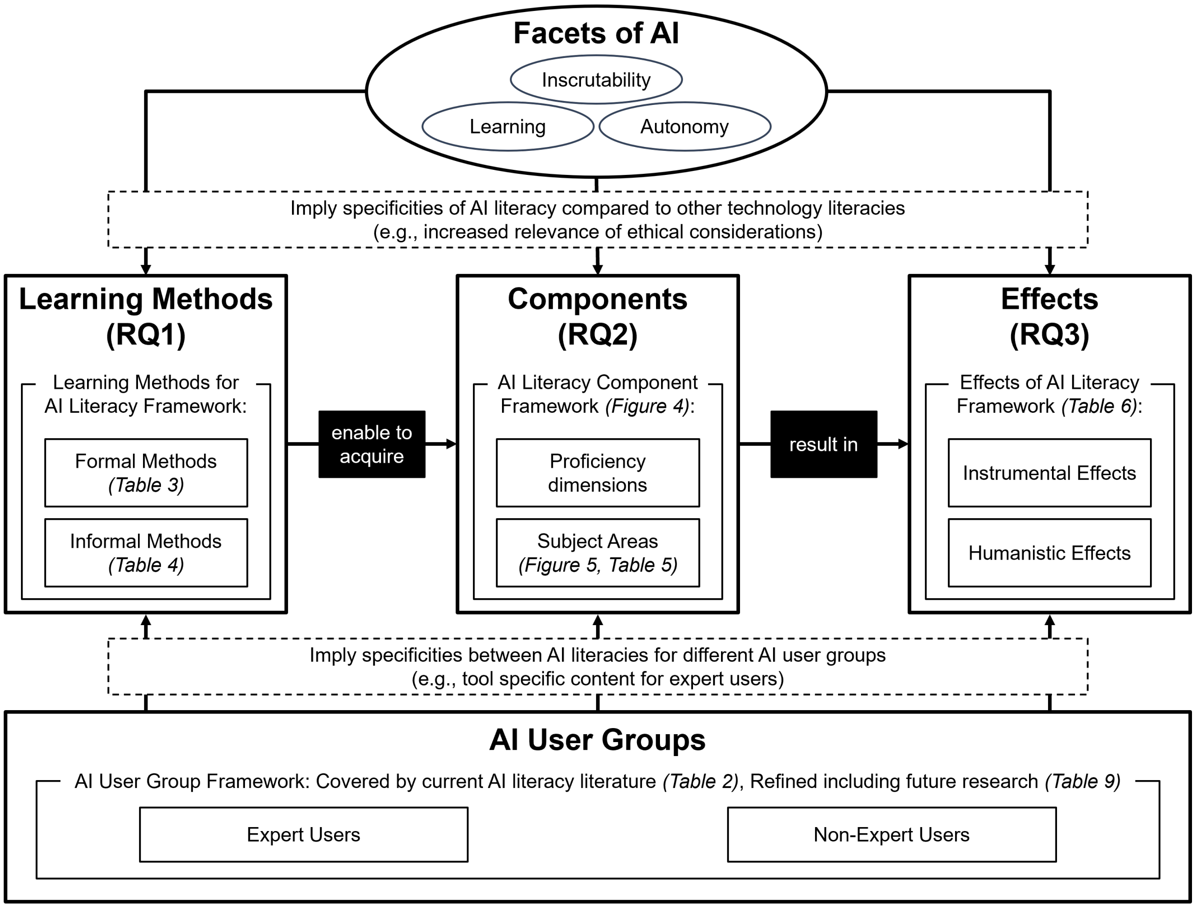

Figure 2.3: *Overarching Conceptual Framework*

existing technology instead of active creation (Meske et al., 2020). Due to the breadth of AI technologies, there is a broad scope of different AI user groups (Berente et al., 2021). In contrast to prior technology, AI technology usage is also not always conscious, extending the scope further. Since AI technology can operate without an artificial interface, which was necessary for previous technology usage, one can use AI without realizing it (Schuetz & Venkatesh, 2020). We have identified two main AI usage domains to structure this broad scope of AI user groups: Expert and non-expert users (Table 2.2). With this understanding, we define AI users as individuals who use autonomous, self-learning, or inscrutable technology (i.e., AI), consciously or unconsciously, in an expert or non-expert context to achieve various objectives.

Within the non-expert context, AI users can also be regarded as "personal users" or "lay users." They require AI literacy to use everyday AI tools, such as AI-powered applications on smartphones, self-driving vehicles, and customer service chatbots (D. Wang et al., 2019). However, it is crucial to acknowledge that AI usage by non-experts increasingly affects society as a whole, exemplified by the impact of AI-powered social media on political processes, such as democratic elections (Fujiwara et al., 2021). The "Cambridge Analytica Scandal" recently showed the critical influence of targeted, AI-powered advertising on society, exposing the need for AI-literate social media users (Isaak & Hanna, 2018). Consequently, non-expert AI usage also carries societal responsibilities for lay users, encompassing all members of society. Within the non-expert context, the literature either focuses on students (including children) (e.g., Kandlhofer et al., 2016; Melsión et al., 2021; W. Yang, 2022) or follows a general approach (implicitly focusing on adults) (e.g., Carolus, Koch, et al., 2023; Kusuma et al., 2022; Register and Ko, 2020). Therefore, we summarize these as a *student* and an *adult* user group, recognizing their differing needs regarding learning methods and AI literacy components as well as the effects AI literacy has on them. Literature focusing on students includes kindergarten and K-12 because integrating AI education into curricula is essential for fostering an AI-literate future generation (e.g., Casal-Otero et al., 2023). As a complement, studies on adults consider the needs of those who have not received an AI education yet or require reskilling (e.g., Long, Blunt, and Magerko, 2021).

Within the expert context, AI users are typically "domain experts" in an organization engaging with specialized AI systems tailored to specific use cases. For instance, a medical doctor utilizing an AI system for cancer detection falls under this category (Jussupow et al., 2021). A comprehensive and parsimonious system organizing the organizational context is the North American Industry Classification System (NAICS, 2023), which facilitates a structured assessment of the existing literature on different AI expert user groups. NAICS codes unmatched by the literature expose unexplored user groups and will be assessed regarding their relevancy for future research directions. AI expert user groups explored by the literature include, for example, teachers (e.g., Kim and Kwon, 2023), managers (e.g., Jorzik et al., 2023), construction workers (Maitz et al., 2022) or librarians (Cox & Mazumdar, 2022). Overall, AI is increasingly relevant to users in both the non-expert and expert contexts. Understanding and addressing the specific needs of AI users in these diverse domains are essential for promoting effective AI literacy and responsible AI usage across society and the economy.

2.4.2 Learning Methods for AI Literacy

Due to AI's rapid development, it is essential to understand the most effective learning methods for equipping different AI users (Long, Padiyath, et al., 2021). Studies covering

Context	Domain	Eco. Activity NAICS code[1]	AI user groups	Sources
Non-expert (Personal context)	Student	-	Students (K-12)	Kandlhofer et al. (2016); Khalid et al. (2022); Kong et al. (2021); I. Lee et al. (2021); Long et al. (2022); Melsión et al. (2021); Ng et al. (2022); Steinbauer et al. (2021); Su et al. (2023); Xu and Babaian (2021); W. Yang (2022)
	Adult	-	Adults	Carolus, Augustin, et al. (2023); Chaudhury et al. (2022); Chiang and Yin (2022); Kusuma et al. (2022); Laupichler, Aster, and Raupach (2023); Leichtmann et al. (2023); Long, Blunt, and Magerko (2021); Long et al. (2019); Long and Magerko (2020); Long, Padiyath, et al. (2021); Markauskaite et al. (2022); Ng et al. (2021); Register and Ko (2020); Salazar-Gomez et al. (2022); Schneider et al. (2023)
Expert (Organizational context)	Construction and Energy	21-23	Construction workers	Charow et al. (2021); Maitz et al. (2022)
	Manufacturing	31-33	Mechanical engineers	Pillay et al. (2018)
	Information	51	Librarians	Cox and Mazumdar (2022)
	Management	55	Managers	Jorzik et al. (2023); Pinski, Hofmann, and Benlian (2023); Pinski, Hofmann, and Benlian (2024); J. Yang et al. (2021)
	Education	61	Teachers	Kim and Kwon (2023)
	Healthcare	62	Medical doctors	Charow et al. (2021); Jussupow et al. (2021)
	Arts, Entertainment, and Recreation	71	Journalists	Deuze and Beckett (2022)
	Unspecified Sector	-	Workers in general	Cetindamar et al. (2022)

1. Unmatched NAICS codes examined in future research directions (see Table 2.11)

Table 2.2: *AI User Group Framework: Covered by Current AI Literacy Literature*

learning methods for AI literacy constitute a significant part of the current academic discourse (37% of the identified corpus, n = 25). The trend of AI permeating into society can also be observed regarding the variety of learning methods, which already go far beyond traditional classroom settings (e.g., Casal-Otero et al., 2023) and include learning in public places, such as museums (e.g., Long, 2023).

The learning literature distinguishes between two learning types that can purposefully structure the learning methods for AI literacy: formal and informal learning (Folkestad, 2006; Manuti et al., 2015; Steinbauer et al., 2021). Formal learning occurs through structured, planned activities and usually takes place in classroom-based educational settings (Marsick & Watkins, 2001). Often seen as the learning standard paradigm, it follows characteristics such as designated teachers, awarded qualifications, and external outcome specifications (Eraut, 2000). In contrast, informal learning is often referred to as what is not formal learning (Colley et al., 2002). Informal learning frequently becomes part of daily routines and is a rather unconscious process, sometimes subject to chance (Marsick & Watkins, 2001). Furthermore, it involves an inductive cycle of reflection and action and is closely connected to learning from others (Marsick & Watkins, 2001).

Regarding AI literacy, both types can be observed within the existing literature. A thorough understanding of both is crucial to determine in which context which AI user group can benefit most from which method. Furthermore, developing a toolkit that allows combining methods into tailored teaching approaches will be essential for AI learning (Markauskaite et al., 2022).

2.4.2.1 Formal Learning Methods for AI Literacy

Based on the identified literature corpus, we structured formal learning methods for AI literacy into three subtypes: lecture-, exercise-, and artifact-based learning (see Table 2.3). Especially regarding formal learning methods, it is important to note that individual learning methods can also appear in combination with other learning methods. For example, lectures are often paired with homework assignments at formal educational institutions (e.g., Xu and Babaian, 2021).

Along with early thinking about AI literacy, the literature discussed well-known learning methods, such as traditional lectures in a weekly or block format (Kandlhofer et al., 2016; Xu & Babaian, 2021). *Lecture-based learning* as a method is not specific to AI. Instead, the content discussed within the respective lectures is specific to the different AI literacy areas. The type of method has predominantly been discussed in a student context (Kandlhofer et al., 2016). The literature divides the *exercise-based learning* subtype into traditional and interactive exercises (e.g., Khalid et al., 2022; Kong et al., 2021; Xu and Babaian, 2021). These exercises are similar to lecture-based learning methods not specific to AI but can convey AI-specific content that relates to AI's learning abilities, increased autonomy, and inscrutability. Traditional exercises achieve this by requiring students to apply AI concepts individually in homework assignments, in-class exercises, or term projects (Xu & Babaian, 2021). Further research conceptualizes interactive exercises, such as group projects or flipped classrooms, a learning method that places the introduction of all AI course materials outside of classes, using the available time in class exclusively for inquiry, application, and assessment of learning materials together with the teacher (Kong et al., 2021). Other studies use story-telling exercises to teach AI specificities (Kandlhofer et al., 2016; Khalid et al., 2022; Ng et al., 2022). To tell a story that involves AI, learners must understand how an AI might work and then organize and analyze their understanding to produce a narrative (Ng et al., 2022). When building their story, learners are encouraged to assess how AI might impact everyday human living (Wong et al., 2020).

Unlike these more generic learning methods tailored to AI content, *artifact-based learning* utilizes AI as part of the learning method. Different studies explored how learners can comprehend AI concepts by interacting with AI-based learning artifacts. Melsión et al. (2021) investigated how explainable AI models (XAI) can be utilized to convey AI specificities, such as gender biases, by showing learners visualizations during an interaction in which an AI model is trained. Other examples include interactions with an online facial recognition AI that lets users find a look-alike from a database of portraits from the US Civil War (Kusuma et al., 2022). Kusuma et al. (2022) create an educational interaction by deliberately designing features that provide context about the dataset's composition and origins, gradually explaining the steps for the AI predictions, and actively involving the user to speculate about the implications of facial recognition in the real world. Next to pure interaction, many studies also proposed the construction of AI tools (e.g., Chiang and Yin, 2022; Kandlhofer et al., 2016; Steinbauer et al., 2021). Building on constructionism learning theory (Papert, 1993), these methods aim to convey AI literacy by constructing either hardware- or software-related AI tools (Kandlhofer et al., 2016). For example, Chiang and Yin (2022) let learners construct customized test datasets to evaluate an AI model's performance, enabling them to experience how the same model performs on different data sets.

2.4.2.2 Informal Learning Methods for AI Literacy

Based on the identified corpus of literature, we structured informal learning methods for AI literacy into three subtypes: community-based, self-directed exercise-based, and self-directed artifact-based learning (see Table 2.4). These informal learning methods have in common that no instructor is present at the time of learning and that they rely

Subtype (1)	**Subtype (2)**	**Examples**	**AI specificity**	**Sources** (By AI User Group)
Lecture-based	-	Lectures (weekly), research camp (block format)	AI-specific content	*Students*: Kandlhofer et al. (2016), Xu and Babaian (2021)
Exercise-based	Traditional exercises	In-class exercises, homework assignments, term projects	AI-specific content	*Students*: Xu and Babaian (2021)
	Interactive exercises	Group projects, flipped classroom, Story-telling about AI	AI-specific content	*Students*: Kong et al. (2021)
Artifact-based	Interaction	Interacting with AI tools, Learning with explainable AI tools	AI is part of the learning artifact	*Students*: Kandlhofer et al. (2016), Khalid et al. (2022), Melsión et al. (2021), Ng et al. (2022) *Adults*: Kusuma et al. (2022)
	Construction	Training of AI models (software), construction of robots with AI features (hardware)	AI is part of the learning artifact	*Students*: Kandlhofer et al. (2016), Burgsteiner et al. (2016), Druga et al. (2019) *Adults*: Chiang and Yin (2022), Ng et al. (2021)

Table 2.3: *Learning Methods for AI Literacy Framework: Formal Methods*

on the learners themselves initiating the learning rather than an educational institution governing the learning. *Community-based learning* is characterized by a shared learning experience with other learners and an exchange on the topic of AI (Druga, 2023; M. Lee & Park, 2022; Long et al., 2022). These can include face-to-face learning in the form of a book club, which focuses on adults (M. Lee & Park, 2022), or a family learning talk, which focuses on children and adults (Druga, 2023; Long et al., 2022). However, learners can also engage in online communities, such as discussion forums, to expand their AI literacy (Chaudhury et al., 2022). In self-directed exercise-based learning, learners seek exercises to further their AI literacy. This includes mobile learning applications (Pinski, Haas, & Franz, 2023) or online resources (Chaudhury et al., 2022) built to facilitate small exercises regarding AI. Both community- and *self-directed exercise-based learning* are only AI-specific regarding the content taught and have been conceptualized mostly for adults or families (see Table 2.4).

In contrast, *self-directed artifact-based learning* often leverages AI as part of the learning artifact to convey AI literacy (e.g., Long, Blunt, and Magerko, 2021). We find that self-directed artifact-based learning methods focused on interaction and construction, similar to the division within formal artifact-based learning methods. Informal learning methods focused on artifact interaction are situated in diverse settings, such as museums (Long, Blunt, & Magerko, 2021; Long et al., 2019) or at home (Ng et al., 2021). For instance, Long, Blunt, and Magerko (2021) developed a public museum exhibit called "LuminAI" that lets learners dance with an AI-generated projection in order to comprehend how the AI could learn from the learners' movements. Some informal learners also aim to construct an AI themselves to acquire AI literacy in a self-directed way (Chaudhury et al., 2022). Chaudhury et al. (2022) find that a common self-directed artifact-based learning method is for some informal learners to pursue "pet projects." By creating an AI tool "as a hobby," enabled through AI literacy acquired via an online course or other self-directed resources, informal learners hope to better understand the topic. However, J. M. Carroll and Rosson (1987) point out that self-directed learning can come with drawbacks, like a focus on quick results that might lead to only a superficial grasp of the subject (production bias). Additionally, learners' prior educational backgrounds play a role in their learning approach, such as favoring math-related AI courses for those with a math background (assimilation bias).

Subtype (1)	**Subtype (2)**	**Examples**	**AI specificity**	**Sources** (By AI User Group)
Community-based	-	Book club, family learning talk, online community forums	AI-specific content	*Families*: Druga (2023), Long et al. (2022) *Adults*: Chaudhury et al. (2022), I. Lee et al. (2022)
Self-directed exercise-based	-	Mobile learning applications, self-chosen exercises	AI-specific content	*Adults*: Chaudhury et al. (2022), Pinski, Haas, and Franz (2023), Pinski, Haas, and Benlian (2024)
Self-directed artifact-based	Interaction	Interactive museum exhibits, interactive home learning artifacts, interaction with online AI tools	AI is part of the learning artifact	*Adults*: Long et al. (2019), Long, Blunt, and Magerko (2021), Long, Padiyath, et al. (2021), Ng et al. (2021)
	Construction	Development of "pet projects," usage of AI for programming simulations	AI is part of the learning artifact	*Adults*: Chaudhury et al. (2022), Ng et al. (2021)

Table 2.4: *Learning Methods for AI Literacy Framework: Informal Methods*

2.4.3 Components of AI Literacy

The literature views AI literacy as a holistic concept of human proficiency regarding a specific type of technology with the facets of autonomy, learning, and inscrutability (see Table 2.1). A large part of the current academic discourse (68% of the identified corpus, n = 46) focuses on exploring and conceptualizing the components of this holistic proficiency concept. When conceptualizing AI literacy as a holistic proficiency concept, the literature can be organized into AI literacy *proficiency dimensions*, such as knowledge, skill, or experience (e.g., Cheney et al., 1990; Marcolin et al., 2000); and AI literacy *subject areas*, which relate to the content of the respective proficiency dimension, such as AI models, data for AI, AI tools (e.g., Long and Magerko, 2020). While current conceptualizations identify highly relevant components (Carolus, Koch, et al., 2023; Laupichler, Aster, Haverkamp, & Raupach, 2023), they do not differentiate between proficiency dimensions and subject areas or focus on particular subject areas, thereby lacking those other researchers identified (i.e., they present a relevant but incomplete picture). Figure 2.4 summarizes the identified proficiency dimensions and subject areas from the literature included in our component conceptualization. Some AI literacy subject areas are more prone to be associated with a certain dimension of proficiency, such as knowledge about AI model types or skills in AI tool recognition. However, there are no "1:1" relationships, and, in principle, all AI literacy proficiency dimensions can relate to all subject areas. For example, one might have knowledge about how to recognize AI tools and also experience and skill in such recognition. The interconnections between the proficiency dimensions and subject areas in Figure 2.4 represent their complex, multilateral relationships.

2.4.3.1 Proficiency Dimensions

Accounting for the scope of prior technology literacies (Subsection 2.2.2) and the different definitions of AI literacy in the literature (see Table 2.1), we find that AI literacy as a holistic and enabling construct comprises different human proficiency dimensions. In the following, we will review the proficiency dimensions that the literature has attributed to AI literacy and what the characteristics of these proficiencies are. Despite some of the existing literature using these proficiency dimensions inconsistently, we aim to adhere to established definitions to structure the proficiency dimension discussed in the current literature.

Knowledge is a core proficiency dimension of AI literacy (Dai et al., 2020; Deuze & Beckett, 2022). It encompasses an understanding of the content and information concerning a subject area. Usually, it is obtained via studying in formal education (Cheney et al., 1990). Multiple studies include *Awareness* as a distinct proficiency

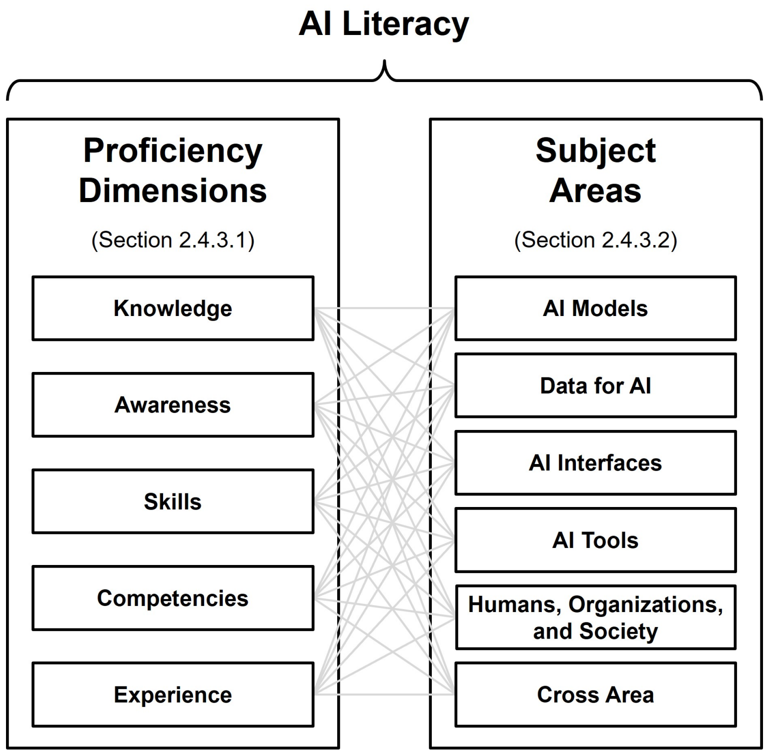

Figure 2.4: *AI Literacy Component Framework*

dimension (Deuze & Beckett, 2022; Heyder & Posegga, 2021; I. Lee et al., 2021). Awareness also includes an understanding of a particular topic but is more focused on the acknowledgment of its existence and relevance at the given time (Merriam-Webster, 2023). *Skills* are integral to effective AI literacy, encompassing psychomotor processes and the ability to execute specific tasks with precision (Cheney et al., 1990; Markauskaite et al., 2022). They also include the capacity to choose the actions most suited for a given scenario from a repertoire of available actions (Cheney et al., 1990). Skills are considered part of AI literacy, primarily for working with AI tools in human-AI collaborations (Dai et al., 2020; Pinski & Benlian, 2023). Most AI definitions draw on the term *Competence* or *Competencies*, synonymous with ability (Carolus, Koch, et al., 2023; Laupichler, Aster, & Raupach, 2023; Long & Magerko, 2020; Ng et al., 2021). The OECD (2019, p. 98) views competence as applying knowledge and skills, referring to "the application and use of knowledge and skills in common life situations." The Joint ACM/AIS IS2020 Task Force et al. (2021, p. 35) echo this notion, stating that such a definition of competence acknowledges "cognitive and metacognitive skills, demonstrated use of knowledge and applied skills, and interpersonal skills that often work in concert." Last, Pinski and Benlian (2023) attribute *Experience* in interaction with AI tools to AI literacy. By interacting with AI tools, one learns "hands-on." Thus, experience often leads to the buildup of tacit knowledge, which, as opposed to explicit knowledge, cannot be codified (Bassellier et al., 2015).

In conclusion, AI literacy emerges as a multifaceted construct that encompasses the proficiency dimensions of knowledge, awareness, skills, competencies, and experience. These proficiency dimensions collectively contribute to the enabling and human-focused AI literacy construct.

2.4.3.2 Subject Areas

The majority of the current literature on AI literacy is concerned with identifying different AI literacy subject areas. AI literacy subject areas denote the content of specific proficiency dimensions, such as knowledge about different AI models. To provide a comprehensive account of the AI literacy subject areas assessed so far, we based our AI literacy subject area conceptualization on a bottom-up assessment of the identified literature corpus. We validated our bottom-up AI literacy subject area conceptualization by assessing related concepts, such as the "Competency Model for Undergraduate Programs in Information Systems" jointly published by the ACM and AIS to unify wording and ensure compatibility (The Joint ACM/AIS IS2020 Task Force et al., 2021).

As a result, we conceptualized five core AI literacy areas ("AI Models," "Data for AI," "AI Interfaces," "AI Tools," "Humans, Organizations, and Society") as well as one "Cross Area," referring to second-level literacy in an AI literacy subject area framework (see Figure 2.5 for an overview, Tables 2.5, 2.6, and 2.7 for the detailed account). Research investigating the interaction of humans and technology looks into their social aspects (i.e., relating to the involved humans) as well as their technical aspects (i.e., relating to the involved technology). However, different aspects do not belong strictly to either side; rather, they fall along a socio-technical continuum (Bostrom et al., 2014; Sarker et al., 2019). The five core subject areas can be organized along this socio-technical continuum, addressing proficiency in different subject areas of the discipline. Whereas *AI Models* and *Data for AI* are rather technical AI literacy areas, *AI Interfaces* connect this AI technology to humans. *AI Tools* instantiate AI as technology in a social context, while *Humans, Organizations, and Society* refer to literacy regarding the social context of AI. The *Cross Area* relates to each core area and involves second-level content, such as knowledge about ethics, which can relate to AI Models but also to Data for AI and every other core area. In the following, we review the current literature within each of the six conceptualized AI literacy subject core areas, including its subareas. Moreover, we assess the subareas' AI-specificity as well as the user groups that have been covered in each subarea.

The conceptualized AI literacy subject area framework has several applications. First, it describes the breadth of AI literacy subject areas and their relationship to each other (i.e., cross vs. core areas). Furthermore, it provides a blueprint to define user-specific AI literacy requirements profiles. Different users necessitate different depths along the subject area dimensions.

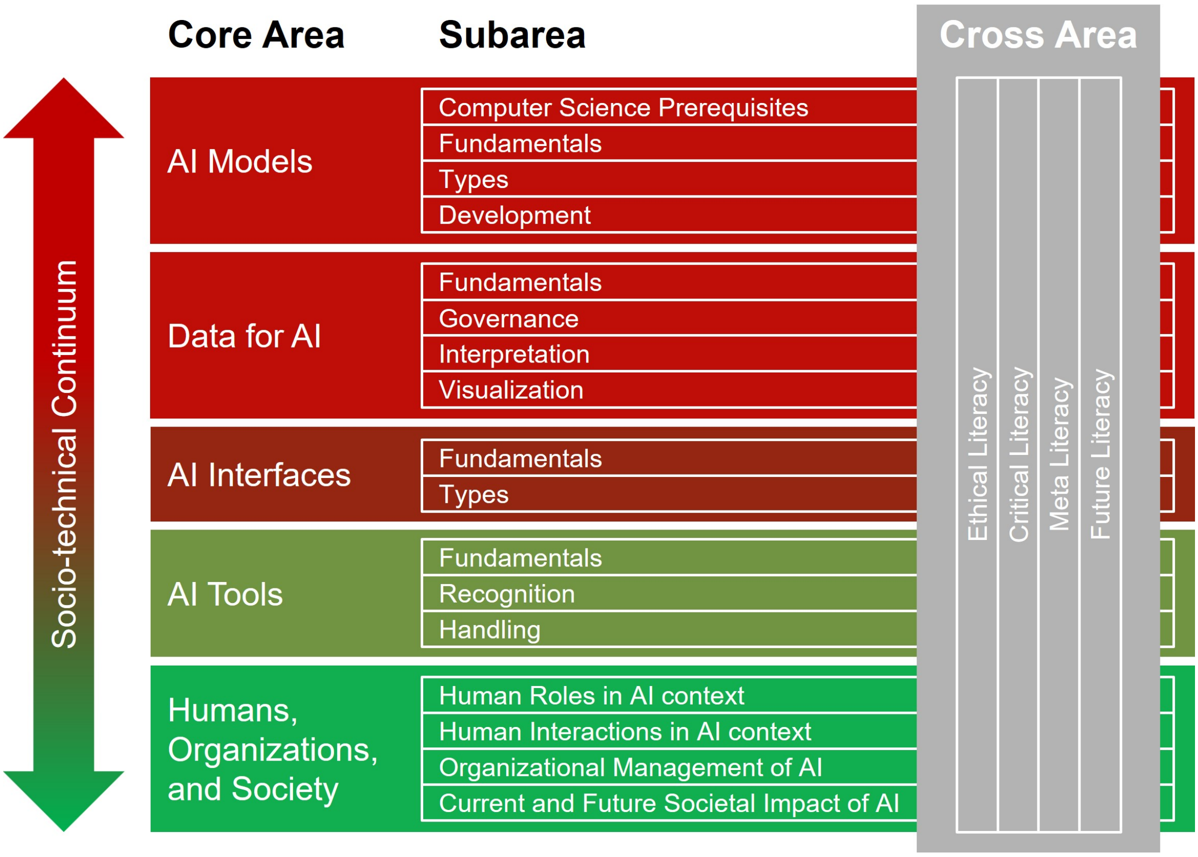

Figure 2.5: *AI Literacy Subject Area Framework (Overview)*

Area	Subarea	Description	AI Specificity	Sources by AI User Group
AI Models	Computer Science Prerequisites	Essential concepts, including abstraction, programmability, algorithmic thinking, basic statistics, and IT infrastructure needed for AI comprehension.	*Not AI-specific*: However, crucial to comprehend AI specificities.	*Students*: Kandlhofer et al., 2016; Khalid et al., 2022; S. Liu and Xie, 2021; Xu and Babaian, 2021; *Adults*: Laupichler, Aster, and Raupach, 2023; Long and Magerko, 2020; Long, Padiyath, et al., 2021; Ng et al., 2021; *Medical doctors*: Charow et al., 2021; Wiljer and Hakim, 2019; *Workers in general:* Salazar-Gomez et al., 2022
	Fundamentals	Understanding the nature of various forms of intelligence (human, animal, machine); differentiating AI from non-AI technology; grasping how AI functions, makes decisions, represents knowledge; and acknowledging AI's strengths and weaknesses.	*AI-specific*: Content describes the differences between non-AI and AI models.	*Students*: Kandlhofer et al., 2016; Khalid et al., 2022; I. Lee et al., 2021; Ng et al., 2022; Xu and Babaian, 2021; *Adults*: Carolus, Koch, et al., 2023; Laupichler, Aster, and Raupach, 2023; Laupichler et al., 2022; Long, Padiyath, et al., 2021; Long and Magerko, 2020; Long, Blunt, and Magerko, 2021; *Managers*: Jorzik et al., 2023; *Medical doctors*: Charow et al., 2021; *Teachers*: I. Lee et al., 2022; *Workers in general*: Cetindamar et al., 2022; Salazar-Gomez et al., 2022
	Types	Understanding the differences between machine learning, deep learning, explainable AI (XAI), and generative AI models, among others, as manifestations of AI concepts and knowledge representations.	*AI-specific*: Content describes the degree of inscrutability, learning, and autonomy of different AI models.	*Students*: Kandlhofer et al., 2016; Khalid et al., 2022; Su et al., 2023; Xu and Babaian, 2021; W. Yang, 2022; *Adults*: Chiang and Yin, 2022 Laupichler, Aster, and Raupach, 2023; Long, Padiyath, et al., 2021; Long and Magerko, 2020; Long, Blunt, and Magerko, 2021; *Teachers*: M. Lee and Park, 2022
	Development	While not mandatory for AI users, appreciating how AI models are constructed provides a deeper comprehension; it is deemed valuable for specific user groups and applications but not essential for all.	*AI-specific*: Content describes steps involved in developing AI models.	*Adults*: Carolus, Augustin, et al., 2023
Data for AI	Fundamentals	Understanding of data structures, data sanitization, and the significance of data for various AI technologies, including the connection between input data and AI model predictions.	*AI-specific*: Content describes how the relationship between data and technology changes through AI; significance of existing processes increased through AI.	*Adults*: Chiang and Yin, 2022; Kusuma et al., 2022; Laupichler, Aster, and Raupach, 2023; Long, Blunt, and Magerko, 2021; Long and Magerko, 2020; Schneider et al., 2023; *Medical doctors*: Charow et al., 2021; *Teachers*: Olari and Romeike, 2021; *Workers in general*: Cetindamar et al., 2022
	Governance	Understanding of control and authority over data management.	*Not AI-specific*: However, increased relevance through AI due to increased amounts of data.	*Medical doctors*: Wiljer and Hakim, 2019; *Workers in general*: Salazar-Gomez et al., 2022
	Interpretation	The ability to appropriately interpret output data from AI systems, recognize potential biases, and understand that output data.	*Not AI-specific*: However, increased relevance through AI due to more potential biases.	*Students*: Melsión et al., 2021; *Adults*: Chiang and Yin, 2022; Long and Magerko, 2020; Long, Padiyath, et al., 2021
	Visualization	An understanding of how to visualize complex AI-generated results to comprehend and effectively utilize the outcomes of AI technologies.	*Not AI-specific*: However, increased relevance through AI due to increasingly more complex results to be understood and communicated.	*Students*: Kandlhofer et al., 2016; *Medical doctors*: Charow et al., 2021; Wiljer and Hakim, 2019; *Workers in general*: Salazar-Gomez et al., 2022

Table 2.5: *AI Literacy Subject Areas (1/3)*

Area	Subarea	Description	AI Specificity	Sources by AI User Group
AI Interface	Fundamentals	Comprehending how AI technologies interact with the physical world and environment, including distinguishing between the AI model (software) and its physical interfaces (hardware) to understand their connection to humans.	*AI-specific*: Content describes how AI interfaces can differ from non-AI interfaces, e.g., through natural communication like voice.	*Students*: Khalid et al., 2022; Xu and Babaian, 2021; *Adults*: Long and Magerko, 2020; *Workers in general*: Salazar-Gomez et al., 2022
	Types	Users need to understand the range of AI interface types, including sensors and software interfaces, to recognize how AI technologies interact with the world and receive input from users.	*AI-specific*: Content describes how AI interfaces differ from each other.	*Adults*: Long, Blunt, and Magerko, 2021; Long and Magerko, 2020; Ng et al., 2021; *Teachers*: I. Lee et al., 2022
AI Tools	Fundamentals	Understanding the instantiation of AI models in specific (social) contexts in the form of AI tools and assessing which human problems can be addressed with specific AI tools.	*AI-specific*: Content describes fundamentals of AI tools having the facets of inscrutability, learning, and autonomy.	*Students*: Kandlhofer et al., 2016; Kong et al., 2021; *Adults*: Laupichler, Aster, and Raupach, 2023; *Medical doctors*: Charow et al., 2021
	Recognition	Being able to identify where AI tools are used and to recognize them during interaction as they increasingly imitate humans and interact through natural communication.	*AI-specific*: Content describes how AI tools are potentially more difficult to recognize because they are more autonomous than non-AI.	*Students*: Ali, DiPaola, Lee, Hong, and Breazeal, 2021; *Adults*: Laupichler, Aster, and Raupach, 2023; Long, Padiyath, et al., 2021; Long and Magerko, 2020;
	Handling	Efficiently handling AI tools includes, among others, understanding the tools' function range and managing privacy during interactions.	*AI-specific*: Content describes how to handle AI tools that are autonomous, can learn, or are inscrutable.	*Students*: Ng et al., 2022; *Adults*: Carolus, Augustin, et al., 2023; Laupichler, Aster, and Raupach, 2023; *Managers*: Jorzik et al., 2023; *Workers in general*: Cetindamar et al., 2022; Salazar-Gomez et al., 2022
Humans, Organizations, and Society	Human Roles in AI Context	Understanding the various roles humans play in relation to AI tools, including programmers, data providers, evaluators, and those affected by AI tools, and their influence on AI tool development and implementation.	*AI-specific*: Content describes how AI interfaces can differ from non-AI interfaces, e.g., through natural communication like voice.	*Adults*: Laupichler, Aster, and Raupach, 2023; Long and Magerko, 2020; Long, Padiyath, et al., 2021; *Workers in general*: Cetindamar et al., 2022
	Human Interactions in AI Context	Collaborating and communicating with other human stakeholders involved in AI projects, teaching and explaining AI concepts to various stakeholders, and managing the impacts of AI interactions.	*AI-specific*: Content describes how interactions with other human stakeholders are altered due to AI's inscrutability, learning, and autonomy.	*Students*: S. Liu and Xie, 2021; *Adults*: Carolus, Augustin, et al., 2023; *Journalists*: Deuze and Beckett, 2022; *Medical doctors*: Charow et al., 2021
	Organizational Management of AI	Effectively managing AI tools within organizations, including understanding their impact on processes, developing AI strategies, anticipating economic and legal implications, identifying opportunities, and recognizing potential impacts on organization members.	*AI-specific*: Content describes how organizations are impacted differently by AI's inscrutability, learning, and autonomy.	*Students*: Kandlhofer et al., 2016; *Adults*: Laupichler, Aster, and Raupach, 2023; *Journalists*: Deuze and Beckett, 2022; *Managers*: Jorzik et al., 2023; *Medical doctors*: Charow et al., 2021; Wiljer and Hakim, 2019; *Workers in general*: Salazar-Gomez et al., 2022
	Current and Future Societal Impact of AI	Comprehending AI's societal implications enables citizens to be aware of AI's influence on democratic societies, anticipate future impacts, and engage in informed debates about AI technology implementations.	AI-specific: Content describes how societies are impacted differently by AI's inscrutability, learning, and autonomy.	*Students:* Eguchi et al., 2021; *Adults*: Laupichler, Aster, and Raupach, 2023

Table 2.6: *AI Literacy Subject Areas (2/3)*

Area	Subarea	Description	AI Specificity	Sources by AI User Group
Cross Area	Ethical Literacy	Understanding and addressing ethical issues and risks related to AI, such as misinformation, diversity, and employment, across AI models, data, and tool implementation in organizations.	*Not AI-specific*: However, increased relevance due to the severity of AI's impact on ethical matters.	*Students*: I. Lee et al., 2021; Melsión et al., 2021; Su et al., 2023; Xu and Babaian, 2021; *Adults*: Laupichler, Aster, and Raupach, 2023; Long and Magerko, 2020; Markauskaite et al., 2022; Ng et al., 2021; *Medical doctors*: Charow et al., 2021; *Teachers*: M. Lee and Park, 2022
	Critical Literacy	Ability to critically assess all core areas, such as AI models, tool outputs, usage needs, and the impact of AI tools.	*Not AI-specific*: However, increased relevance due to AI's complexity.	*Adults*: Carolus, Augustin, et al., 2023; Laupichler, Aster, and Raupach, 2023; Laupichler et al., 2022; Register and Ko, 2020; *Medical doctors*: Charow et al., 2021
	Meta Literacy	Being aware of one's own AI literacy level.	*Not AI-specific*: However, increased relevance due to AI's increasing human-like capabilities.	*Adults*: Chaudhury et al., 2022; Fügener et al., 2021a
	Future Literacy	Recognizing the dynamic evolution of AI and envisioning its future impact on AI literacy requirements as well as cultivating the learning skills to adapt to these requirements.	*Not AI-specific*: However, increased relevance due to AI's rate of change.	*Students*: I. Lee et al., 2021; *Adults*: Long and Magerko, 2020; Markauskaite et al., 2022; Ng et al., 2021; *Workers in general*: Cetindamar et al., 2022

Table 2.7: *AI Literacy Subject Areas (3/3)*

Core Area 1: AI models. Different studies emphasize that a certain extent of *computer science prerequisites* is necessary to comprehend AI models (e.g., Khalid et al., 2022; Laupichler, Aster, and Raupach, 2023; Salazar-Gomez et al., 2022). While these fundamentals are not AI-specific, the literature seems to view them as a crucial overlap, which led us to include them in the conceptualization. As such, different studies include core computer science concepts like abstraction (Kandlhofer et al., 2016) or programmability (Long & Magerko, 2020), algorithmic and computational thinking (Khalid et al., 2022; Long, Padiyath, et al., 2021), basic statistics (Wiljer & Hakim, 2019; Xu & Babaian, 2021), and basics regarding IT infrastructure necessary for AI (Salazar-Gomez et al., 2022). Most computer science fundamentals are not user group specific, i.e., relevant for everyone aiming to develop AI literacy. Individual studies emphasize the special significance of various topics for particular user groups, such as biomedical-specific computer science concepts for healthcare professionals (Charow et al., 2021).

AI model fundamentals constitute the essential subarea for understanding how AI models work. In this regard, learners must understand the notions of (artificial) intelligence of various "intelligent" entities, including an understanding of the distinctions between human, animal, and machine intelligence (Long, Blunt, & Magerko, 2021; Long & Magerko, 2020). Furthermore, it entails distinguishing AI from non-AI technology (I. Lee et al., 2021) as well as "general" from "narrow" AI concepts (Laupichler, Aster, & Raupach, 2023; Long & Magerko, 2020). Next to AI concepts, AI model fundamentals include understanding how AI – in principle – functions (Carolus, Koch, et al., 2023; Ng et al., 2021) and derives decisions (Kandlhofer et al., 2016; Long & Magerko, 2020). Learners should comprehend what it means when a model learns (Laupichler, Aster, & Raupach, 2023) and how they respond to the environment (Carolus, Koch, et al., 2023). AI model fundamentals also include recognizing how knowledge is represented within an AI and what limitations these knowledge representations have (Long, Padiyath, et al., 2021; Xu & Babaian, 2021). Lastly, the literature asserts that it is fundamental for AI models to understand their strengths and weaknesses, like greater accuracy than non-AI models, the ability to process unstructured data, or AI's inscrutability (Charow et al., 2021; Laupichler, Aster, & Raupach, 2023).

Beyond a fundamental comprehension of AI models, AI users must also understand how these intelligence concepts, decision-making processes, or knowledge representation materialize in specific *AI model types*. The literature emphasizes the relevance of machine learning (Chiang & Yin, 2022; Khalid et al., 2022) and deep learning models (Kong et al., 2021; Xu & Babaian, 2021). An example of an AI model leveraging deep learning technology is a neural network (Xu & Babaian, 2021). Furthermore, explainable AI (XAI) models, i.e., AI models that are inscrutable but made partially explainable through additional technology, are model types discussed by several scholars (Chiang & Yin, 2022; Laupichler, Aster, & Raupach, 2023). More recently, generative AI models, i.e., AI models capable of generating text, images, or audio, have gained attention (M. Lee & Park, 2022). This subarea is AI-specific since it equips AI users to understand the degree of inscrutability, learning, and autonomy of different AI models. Even though different AI model types constitute already more advanced AI literacy, the literature agrees that it is relevant for students (Kandlhofer et al., 2016; Khalid et al., 2022) as well as for adult AI users (Chiang & Yin, 2022; Laupichler, Aster, & Raupach, 2023) to build a firm understanding.

AI model development is a counterintuitive subarea in an AI literacy conceptualization focused on AI users. The rationale behind including development as a subarea is that comprehending how things are built enables a more profound understanding of a specific topic, as also expressed by the artifact-based construction learning methods for AI literacy (e.g., Ng et al., 2021). However, AI model development is by no means a requirement for AI users. Carolus, Koch, et al. (2023, p. 6) state that AI model development is "useful for certain user groups and application areas but are not necessary for all users." AI model development can be seen as AI-specific as it involves building AI models.

Core Area 2: Data for AI. Many extant studies emphasize the relevance of understanding data for AI literacy (Cetindamar et al., 2022; Charow et al., 2021). While academics conceptualized data literacy before AI literacy (Wolff et al., 2016), the increased relevance of data for AI compared to non-AI technology closely ties the concepts together, creating overlaps (Olari & Romeike, 2021). As such, the subarea *data fundamentals* entails basic data knowledge, such as data structures or data sanitization, but also an understanding of data's meaning for different AI technologies (Chiang & Yin, 2022; Laupichler, Aster, & Raupach, 2023; Long & Magerko, 2020). Most importantly, the literature emphasizes understanding how input data and predictions are connected in AI models with learning capabilities (Kusuma et al., 2022; Laupichler, Aster, & Raupach, 2023; Long, Blunt, & Magerko, 2021). In that context, Schneider et al. (2023) note that it is a crucial part of AI literacy to understand the impact of data-sharing practices, such as sharing data, not sharing data, or sharing purposefully biased data, on an AI model. Data in itself is not specific to AI. However, the relationship between data and technology has changed through the introduction of AI because technology can now learn from data and is not dependent on experts codifying how technology should behave. Therefore, non-AI-specific processes, like data sanitization, have received an elevated significance.

Exercising control and authority over data management is referred to as *data governance* (Abraham et al., 2019). While it is not AI-specific per se, multiple studies mention its importance for AI literacy (Salazar-Gomez et al., 2022; Wiljer & Hakim, 2019). Since modern AI technologies necessitate enormous amounts of data due to their learning capabilities, managing these increasing data amounts becomes more relevant. Furthermore, AI can increasingly process unstructured data, which leads to new challenges for data governance processes (Vazhayil et al., 2019). For example, the generative AI ChatGPT has been trained on 300 billion words (Hughes, 2023).

Different studies stress the importance of *data interpretation* for AI literacy (Chiang & Yin, 2022; Long & Magerko, 2020; Melsión et al., 2021). When working with AI, users must be able to appropriately interpret the data an AI technology is outputting. That includes, for example, recognizing that output data cannot be taken at face value (Long & Magerko, 2020) and being aware of biases or even the ability to detect potential biases (Melsión et al., 2021). Similar to data governance, data interpretation is not new but has increased significantly in relevance due to AI. Correctly interpreting data is a highly relevant skill due to AI's inscrutability.

Since AI technology can be complex and produces counterintuitive results, *data visualization* is also increasingly important to understand and utilize those results (Kandlhofer et al., 2016; Salazar-Gomez et al., 2022). Users need to be able to understand and present output from AI technologies, for which data visualization is a powerful tool (Charow et al., 2021). However, next to using data effectively for story-telling (Wiljer & Hakim, 2019), users can also utilize data visualization to comprehend better how AI technologies are functioning. In the same vein of data governance and interpretation, data visualization is not AI-specific, but its meaning has increased due to more complex underlying models that need to be understood and communicated.

Core Area 3: AI interfaces. Especially, advances in natural language processing enabled entirely new ways for humans to interact with technology, effectively removing the artificial interface, which was necessary for all non-AI human-technology interaction (Schuetz & Venkatesh, 2020). Therefore, the subarea of *AI interface fundamentals* comprises a basic understanding of how AI technologies can act in the physical world and interact with their environment (Long & Magerko, 2020). For instance, this includes being able to comprehend the differences between the AI model (i.e., software) and its physical interfaces (i.e., hardware) (Khalid et al., 2022). As such, the subarea represents how the more technological areas of AI Models and Data for AI are connected to humans. While having been explored mostly in the personal domain (Khalid et al., 2022; Xu & Babaian, 2021), the subarea is AI-specific because it highlights how AI interfaces differ from non-AI interfaces.

Furthermore, users need to know which different *AI interface types* exist. Several studies highlight an understanding of sensors regarding AI (Long, Padiyath, et al., 2021; Ng et al., 2021; Pinski & Benlian, 2023). Long and Magerko (2020) assert that it is important to recognize what sensors are, that AI technologies use them to observe the world, and that various sensors facilitate various forms of world representation and reasoning. However, understanding AI interfaces extends beyond sensors (Long et al., 2022). Most AI technologies like ChatGPT interact with their users through software interfaces. Therefore, users must understand how different AI technologies receive input through their respective interface types.

Core Area 4: AI tools. With an AI tool (also called “application” by some scholars, Kandlhofer et al., 2016), we refer to the instantiation of an AI model in a specific human context (Long & Magerko, 2020). For example, an AI-based cancer diagnosis tool instantiates the AI model of a neural network in the context of medicine (Tschandl et al., 2020). AI literacy should enable AI users to handle these AI tools proficiently. Such proficient handling requires *AI tools fundamentals*, providing users with an understanding of the connections between different AI models and common AI tools (Charow et al., 2021; Kandlhofer et al., 2016). Furthermore, it entails being able to assess which human problem contexts can be addressed with specific AI tools (Laupichler, Aster, & Raupach, 2023) and which application areas exist for AI (Druga et al., 2022).

AI tool recognition has received a special emphasis from academics because AI tools are increasingly capable of imitating humans (e.g., AI-based chatbots) (Adam et al., 2020), and interaction with AI tools is increasingly facilitated via means of natural human communication (e.g., voice-based AI agents) (Carolus, Koch, et al., 2023). Thus, it has become much more difficult to immediately recognize whether one interacts with an AI tool or a human (Long & Magerko, 2020). Therefore, AI-literate humans should have an understanding of which tools generally are supported by AI technologies, such as natural language processing, and what to look for to recognize one is interacting with an AI (Laupichler, Aster, & Raupach, 2023). While AI tool recognition is an important area of AI literacy, one should note that AI technologies are becoming increasingly more capable of deceiving humans so that, at some point, even highly AI-literate humans might not be able to detect them anymore. However, similar to deep fakes and misinformation on social media, an awareness of where one might be confronted with AI and how one might spot it is paramount (Ali, DiPaola, Lee, Hong, & Breazeal, 2021; Ali, DiPaola, Lee, Sindato, et al., 2021). AI tool recognition is AI-specific because AI tools are potentially more difficult to recognize due to their increased autonomy and learning ability.

A central area of AI literacy is efficient *AI tool handling* (Salazar-Gomez et al., 2022; B. Wang et al., 2022). AI tool handling includes tool-agnostic as well as tool-specific aspects. Independent of the AI tool one uses, one must manage one's own privacy when interacting with the respective AI tool (Carolus, Koch, et al., 2023; Laupichler, Aster, & Raupach, 2023). Specific to an AI tool, its users need to be aware of the function range and how to operate the AI tool correctly and effectively (Carolus, Koch, et al., 2023; Salazar-Gomez et al., 2022). For instance, managers need to know how to utilize AI-based decision-support systems (Jorzik et al., 2023). AI tool handling is AI-specific because it is the AI facets (autonomy, learning, and inscrutability) that make handling AI tools different from handling non-AI tools.

Core Area 5: Humans, organizations, and society. Since AI models are instantiated as AI tools in specific human contexts, AI literacy not only includes proficiency regarding the isolated AI tools but also regarding the humans involved. The literature discusses these human-related AI literacy subject areas on three different levels: the individual human level (Long & Magerko, 2020), the organizational level, such as firms (Jorzik et al., 2023), and the human society as a whole (Laupichler, Aster, & Raupach, 2023). First, being aware of the different individual *Human roles in the AI* context and their respective functions is crucial (Long & Magerko, 2020). For instance, one must acknowledge that humans, in their role as programmers, significantly influence the development choices, model selection, and finetuning of AI tools (Cetindamar et al., 2022; Long & Magerko, 2020). Beyond programmers, there are manifold human roles involved when organizations implement AI tools, such as those who provide data for an AI tool (e.g., customers), those who evaluate and approve an AI tool (e.g., managers or government institutions), or those who are replaced by an AI tool (e.g., customer service agents) (Ali, DiPaola, Lee, Sindato, et al., 2021). AI-literates have a comprehensive understanding of the different roles individuals have in relation to an AI tool (Pinski, Adam, & Benlian, 2023). Such an understanding is AI-specific because the human roles in relation to technology have changed due to, for example, the learning capabilities of AI tools.

Next to knowing the human roles in the AI context, a part of AI literacy is proficiency in *Human interactions in the AI context*. Depending on one's role, this can entail collaborating with other involved human stakeholders of an AI project, such as the developers or business counterparts (Charow et al., 2021). Furthermore, it involves communicating about AI tools and their outputs with other stakeholders, such as patients, in the case of medical doctors using AI tools (Carolus, Koch, et al., 2023; Charow et al., 2021). User groups in the educational sector or leading positions also need the ability to teach and explain AI concepts to other stakeholders (Carolus, Koch, et al., 2023; Deuze & Beckett, 2022; S. Liu & Xie, 2021). The subarea is AI-specific because human interactions are changed due to AI's facets. For example, a doctor might need to communicate an AI-based diagnosis differently than a human diagnosis to a patient to get their buy-in for a specific treatment.

Organizational management of AI is required for many AI users who not only use AI tools directly but manage the broader organizational context in which the AI tool is situated. Medical doctors might use AI-based diagnostic tools and must similarly manage their impact on clinical processes (Charow et al., 2021; Wiljer & Hakim, 2019). Corporate executives are urged to develop an AI vision or strategy to successfully implement AI tools in their firms (Jorzik et al., 2023; Salazar-Gomez et al., 2022). Furthermore, executives must anticipate AI's economic and legal implications in the organizational context (Charow et al., 2021; Laupichler, Aster, & Raupach, 2023). Almost all user groups would benefit from the ability to identify opportunities that AI enables for their organization (Deuze & Beckett, 2022; Pinski, Hofmann, & Benlian, 2023; Salazar-Gomez et al., 2022). Additionally, many studies have shown how collaborating with AI can affect the interacting humans themselves, such as their cognitive processes (Bauer et al., 2021) or attitudes (Pinski, Adam, & Benlian, 2023). As a result, AI literacy also entails knowledge of the potential impacts that AI tools can have on the members of an organization. The subarea is AI-specific because it highlights how technology that is autonomous, can learn, or is inscrutable affects organizations differently.

On the broadest human scale, the *current and future societal impact of AI* is part of AI literacy (Laupichler, Aster, & Raupach, 2023). In the role of a citizen of a democratic society, users of AI technology, such as social media networks powered by AI algorithms, must have an awareness of the potential impacts these technologies might have on society (Markauskaite et al., 2022; Ng et al., 2022; Xu & Babaian, 2021). Furthermore, an imaginative ability to project how a society might be impacted in the future can equip citizens to debate how a society might want to (or deliberately not want to) implement specific AI technologies (Long & Magerko, 2020).

Cross areas. Complementary to the five core areas of AI literacy, the literature discusses several proficiencies that can be described as second-level or cross areas because they relate to each of the core areas in distinct ways, such as *ethical literacy* (e.g., Xu and Babaian, 2021), *critical literacy* (e.g., Register and Ko, 2020), *meta literacy* (e.g., Chaudhury et al., 2022), and *future literacy* (e.g., I. Lee et al., 2021). Individual academics view some of these areas on the same level as the core areas. However, after assessing the collected corpus of AI literacy literature, we conclude that these cross areas are relevant in relation to each core area. The *ethical literacy* cross area enables humans to identify, describe, and deliberate diverse perspectives on ethical issues and risks around AI, such as misinformation, diversity, or employment (Long & Magerko, 2020; Xu & Babaian, 2021). These issues relate to the core areas, such as the AI models, the data used, or the specific implementation of an AI tool in an organization (Charow et al., 2021; I. Lee et al., 2021). Markauskaite et al. (2022) state that it will be a critical human task in the future to ensure that we encode human values into the AI tools that we build. As such, ethical thinking will be necessary for each core area leading up to the AI tools we implement and use and, for example, how they integrate into or replace jobs in the current employment landscape. Ethical literacy has also been relevant before AI and is not AI-specific. However, the ethical challenges have multiplied through the introduction of AI due to its increasing scope (Berente et al., 2021), which significantly increased the necessary proficiency in ethical thinking.

Due to AI's increasing sphere of influence, *critical literacy* is a crucial cross area of AI literacy. AI literates should be able to think critically about the AI models (Register & Ko, 2020) and the output of AI tools (Laupichler, Aster, & Raupach, 2023), evaluate their own usage needs and behaviors (Carolus, Koch, et al., 2023), or critically reflect on the impact of AI tools (Laupichler, Aster, & Raupach, 2023). Before AI, critical literacy has also been relevant. However, due to AI's increased complexity and inscrutability, critically assessing the technology and different aspects of human-AI collaborations has become more prominent.

Following the tradition of metaknowledge, *meta literacy* refers to the awareness of one's own AI literacy (Evans & Foster, 2011). Particularly for informal learners, monitoring and reflecting on their AI literacy is important to become AI-literate when engaging in self-directed learning (Chaudhury et al., 2022). Fügener et al. (2021a) show that awareness of one's own proficiency is crucial in human-AI collaborations. Meta literacy is also not new, but it has increased in relevance due to AI's increasing human-like capabilities, making it more relevant to monitor what one is capable of compared to the technology and what one knows about it (Authors, Forthcoming).

Additionally, scholars assert that one not only needs an awareness of their current AI literacy but also of the needed *future (AI) literacy* (I. Lee et al., 2021; Long & Magerko, 2020). AI is evolving at unprecedented rates (Berente et al., 2021), which also requires AI literacy to adapt constantly. Therefore, AI users will need to imagine what the future of AI might look like (Long & Magerko, 2020) and realize what will be relevant to AI literacy (I. Lee et al., 2021). Furthermore, they must develop the learning skills that allow them to seize this future AI literacy (Cetindamar et al., 2022; Markauskaite et al., 2022). Ng et al. (2021) state that anticipating and realizing future AI literacy requires confidence in one's own learning abilities. Finally, future literacy is also not AI-specific. Nevertheless, due to AI's unprecedented rate of change, it gained significantly in value as part of human technology proficiency.

2.4.4 Effects of AI Literacy on AI Users

The effects of AI literacy are the least researched area of the three examined steps, with 16% (n = 11) of the reviewed papers addressing them. To structure the explored effects, we draw on a categorization of the effect outcome nature into humanistic and instrumental outcomes introduced by Sarker et al. (2019). Literature at the intersection of humans and technology emphasizes that socio-technical research should assess effects on humanistic-oriented outcomes, such as equality and well-being, as well as effects on instrumental-oriented outcomes, such as efficiency and effectiveness (Sarker et al., 2019). On the other hand, AI literacy is often investigated in a context where humans learn, i.e., acquire AI literacy. As such, we also evaluate the so far explored effects along an established framework focused on types of human learning outcome: Kraiger et al. (1993) distinguish the affective, behavioral, and cognitive effect types that learning has on humans. By assessing the effects of AI literacy with these two complementary frameworks, we intend to expose where research has already accumulated and in which dimensions more research is needed (Table 2.8).

The literature investigated various instrumental effects of AI literacy. AI usage continuance intentions are an AI-specific version of general IS continuance intentions

(Bhattacherjee, 2001). The literature presents mixed findings concerning AI literacy and such intentions to continue using AI tools. Pinski, Adam, and Benlian (2023) found a negative association between AI literacy and AI usage continuance intentions after individuals were educated and then interacted with an AI. In another study, Pinski, Haas, and Franz (2023) found a positive association between AI literacy and AI usage continuance intentions after individuals have only been educated on AI.

Looking at the more behavioral-oriented and closely related constructs of appropriate delegation behavior towards AI (Pinski, Adam, & Benlian, 2023) and appropriate reliance on AI (Chiang & Yin, 2022), studies identify a positive association with AI literacy. The literature agrees that AI literacy enhances appropriate behavior toward an AI, e.g., to delegate a certain task or to rely on an AI decision when it is favorable to do so (Chiang & Yin, 2022; Pinski, Adam, & Benlian, 2023). Chiang and Yin (2022) qualify this relationship by showing that it is stronger for individuals with high domain knowledge of the underlying task. Furthermore, appropriate trust in AI – a rather affective and cognitive construct – has been associated positively with AI literacy (Leichtmann et al., 2023). Surprisingly, the same studies find different results as to how AI literacy materializes in the performance of the underlying task. Whereas Pinski, Adam, and Benlian (2023) and Chiang and Yin (2022) find that the overall performance of the human-AI collaboration increased with the behavioral change, Leichtmann et al. (2023) found no effect on the performance.

Pinski, Haas, and Franz (2023) find that increasing individuals' AI literacy in an informal educational setting exhibits an increased (i.e., more positive) attitude toward AI. In contrast, Tully et al. (2023) assert in a survey study across different countries that greater AI literacy leads to decreased AI receptivity (i.e., openness to AI-based products and services). Regarding the perceived intelligence of AI technology, prior research also presents a mixed picture. Whereas Van Brummelen et al. (2021) found that after learning about AI, perceptions about the intelligence of conversational agents increased, Druga and Ko (2021) found that educational interventions regarding AI can also demystify it and reduce intelligence perceptions. On the other hand, AI literacy has been found to increase career awareness, enabling individuals to make informed career choices aligned with the evolving technological landscape (I. Lee et al., 2021). Furthermore, AI literacy enhances career adaptability skills, equipping individuals to navigate AI-driven work environments adeptly (I. Lee et al., 2021).

Humanistic effects have been researched far less than instrumental effects (Table 2.8). Register and Ko (2020) found that AI literacy empowers individuals with the proper knowledge to self-advocate against harmful AI, fostering a sense of agency in safeguarding against adverse AI implications. Melsión et al. (2021) showed that individuals with higher AI literacy possess an increased ability to discern the impact of gender bias, enabling critical evaluation and proactive efforts toward bias mitigation. Overall, the literature tends to support the idea that AI literacy education empowers individuals to achieve humanistic outcomes.

In summary, AI literacy's explored instrumental and humanistic effects are multifaceted, spanning affective, behavioral, and cognitive human learning outcomes. However, we are far from a comprehensive understanding of the effects of AI literacy that shape how humans navigate the intricate landscape of AI. Past research focused predominantly on instrumental effects that mostly relate to cognitive learning outcomes (Table 2.8).

2.5 Discussion

In this study, we conducted a scoping review of research on AI Literacy for users. This section outlines a future research agenda offering six future research directions along the three research questions of the study that have not yet been explored but may provide valuable insights into the field. Furthermore, we describe the study's contributions and limitations.

2.5.1 Future Research Agenda for AI Literacy

By analyzing gaps within the results of our literature review, we deducted research directions for each AI literacy step from the conceptual framework (an overview is available in Table 2.9): Learning methods for AI literacy comprise "I. Include a broader AI user base in the learning method assessment and development" and "II. Evaluate the effectiveness of learning methods concerning AI specificities." Components of AI literacy comprise "III. Solidify a specific understanding of what AI literacy constitutes" and "IV. Refine AI literacy needs for diverse AI user groups." Lastly, the effects of AI literacy comprise "V. Explore the humanistic effects of AI literacy" and "VI. Consider moderating factors to contextualize AI literacy's effects." The future research agenda based on these six future research directions is by no means exhaustive but aims to highlight and demonstrate avenues that look particularly promising to steer the future discourse toward exploring the relevant aspects of AI literacy more specifically.

Nature of effect	Affected construct	Direction	Human learning outcome type A[1]	B[2]	C[3]	Sources
Instrumental	AI usage continuance intention	Mixed findings			×	*Adults*: Pinski, Adam, and Benlian (2023), Pinski, Haas, and Franz (2023)
	Appropriate delegation behavior / reliance	Increase		×		*Adults*: Chiang and Yin (2022), Pinski, Adam, and Benlian (2023)
	Appropriate trust	Increase	×		×	*Adults*: Leichtmann et al. (2023)
	Attitude toward AI	Increase			×	*Adults*: Pinski et al. (2023b)
	Career adaptability skills	Increase			×	*Students*: I. Lee et al. (2021)
	Career awareness	Increase			×	*Students*: I. Lee et al. (2021)I. Lee et al. (2021)
	Perceived intelligence	Mixed findings			×	*Students*: Van Brummelen et al. (2021), Druga and Ko (2021)
	Performance in human-AI collaborations	Mixed findings		×	×	*Adults*: Chiang and Yin (2022), Leichtmann et al. (2023), Pinski, Adam, and Benlian (2023)
	Receptivity toward AI	Decrease	×		×	*Adults*: Tully et al. (2023)
Humanistic	Ability to discern gender bias impact	Increase			×	*Students*: Melsión et al. (2021)
	Ability to self-advocate against harmful AI	Increase			×	*Adults*: Register and Ko (2020)

1. Affective, 2. Behavioral, 3. Cognitive

Table 2.8: *Effects of AI Literacy Framework*

2.5.1.1 Directions for the Learning Methods for AI Literacy

Research Direction I. Include a broader AI user base in the development and assessment of learning methods. Research regarding learning methods has been exclusively focused on non-expert AI users, such as K-12 students (e.g., Kandlhofer et al., 2016), adults in their personal (non-work-related) roles (e.g., Kusuma et al., 2022), or families (Druga, 2023). While these user groups are a viable starting point, the literature agrees that AI literacy also needs to be explored for expert AI user groups (e.g., Jorzik et al., 2023; J. Yang et al., 2021). As such, learning methods to acquire AI literacy must be considered for adults beyond personal roles (e.g., Pinski, Haas, and Franz, 2023) and include expert roles. The requirements for effective learning might differ substantially for individuals in their work-related compared to their personal AI

Type		Future research direction	Exemplary future research questions
Learning methods for AI literacy	I	Include a broader AI user base in the learning method assessment and development.	- Which learning methods are most efficient and effective for workers in transactional relationships with an AI tool to ensure sustainable, efficient, and ethical learning results? - Which learning methods are most successful for workers affected by AI but not directly in contact with AI?
	II	Evaluate the effectiveness of learning methods concerning AI specificities.	- Which learning methods are most effective to build a comprehensive awareness of the ethical implications of AI? - What are AI literacy measurement tools that minimize measurement biases?
Components of AI literacy	III	Solidify a specific understanding of what AI literacy constitutes.	- Which subject areas are essential to gain a specific understanding of AI for using it in the non-expert context? - Which proficiency dimensions of AI literacy are associated with which subject areas most commonly?
	IV	Refine AI literacy needs for diverse AI user groups.	- Which technical AI model aspects help adult non-expert users in their AI interactions, and which excessive technicalities hinder overall comprehension? - Which AI literacy proficiency dimensions and areas are relevant for judges?
Effects of AI literacy	V	Explore the humanistic effects of AI literacy.	- How does AI literacy impact the well-being of humans working in human-AI collaborations? - Which AI literacy subject areas have which effect on human well-being in human-AI collaborations?
	VI	Consider moderating factors to contextualize AI literacy's effects.	- How does the type of AI affect AI literacy's effect on human attitude and receptivity toward AI? - Which moderating factors contribute to AI literacy being positive for humans and which to it being negative?

Table 2.9: *Future Research Agenda*

user roles. After assessing the existing research regarding the respective user groups they address, we can determine which user groups have been omitted thus far and which are particularly promising for future research in the different steps of AI literacy. Therefore, Appendix 2.C (Table 2.11) gives an overview of the AI user groups covered and omitted by the literature in the expert context.

For example, organizations may implement role-specific learning objectives that differ from personal learning objectives because they are much more focused on the proper execution of a particular task rather than a broad consumer-centric understanding. Learning focused on task-specific execution might draw on a specific set of methods to achieve its learning goals. For example, customer service agents utilizing a new knowledge management tool drawing on a large language model to retrieve information for answering customer requests might be better suited to learn through highly practically oriented training exercises. However, it is unclear how much this prepares them to use the tools responsibly. Therefore, it may be interesting to see how learning methods can be combined to convey an ethical understanding of large language models while ensuring task-specific AI proficiency. As such, one potential research question could be, "Which learning methods are most efficient and effective for workers in transactional relationships with an AI tool to ensure sustainable, efficient, and ethical learning results?"

Furthermore, there are many user groups concerning workers who might be affected by AI but who will not work directly with the AI or have no influence over it, such as workers from the transportation sector, like taxi and Uber drivers. This direction prompts the exploration of effective learning methods for workers who may not be directly involved with AI but are impacted by its influence. It might be interesting to investigate how AI literacy can be best conveyed if workers do not directly use AI in their work. As such, another potential research question could be, "Which learning methods are most effective for workers affected by AI but not directly in contact with AI?"

Research Direction II. Evaluate the effectiveness of learning methods concerning AI specificities. Much prior research concerning the learning methods for AI literacy has explored which methods are available to learners, such as mobile apps (Pinski, Haas, & Franz, 2023). However, few studies measure the effectiveness of the learning methods they focus on, while even fewer studies specifically address how they are suitable to convey AI specificities. On the one hand, we urge future research to develop different instruments to evaluate the effectiveness of learning methods. The literature has produced various self-assessment (Likert-type) scales (e.g., Laupichler, Aster, and Raupach, 2023; B. Wang et al., 2022), which are subject to known biases in knowledge self-assessment like the Dunning-Kruger effect (Kruger & Dunning, 1999). There are initial developments toward objective measurements, such as a multiple-choice test (P. Weber, Baum, & Pinski, 2023). However, we urge researchers to develop more diverse instruments to evaluate the effectiveness of learning methods. For example, one could aim for a behavior-based measurement of AI literacy or other innovative test formats. As such, a potential research question could be, "What are AI literacy measurement tools that minimize measurement biases?"

On the other hand, research regarding AI literacy learning methods must aim to focus on AI specificities. Therefore, future research should assess which learning methods or combination of learning methods are particularly suited for comprehending the autonomy, learning, and inscrutability particularities of AI technology as well as their consequences. For example, government-related user groups, such as policymakers or judges, which have not been explored so far (see Appendix 2.C, Table 2.11), should specifically ensure that AI complies with the values of a society (Markauskaite et al., 2022). As such, they necessitate an education geared toward identifying the potential implications resulting from AI's specific characteristics and their impact on the ethical standards of a society. This poses potential research questions like, "Which learning methods are most effective for building a comprehensive awareness of the ethical implications of AI?."

2.5.1.2 Directions for the Components of AI Literacy

Research Direction III. Solidify a specific understanding of what AI literacy constitutes. This review pointed out that AI literacy is a holistic proficiency concept comprising different proficiency dimensions and subject areas. We found that many studies address individual proficiency dimensions (e.g., "set of competencies": Long and Magerko, 2020) or assume an understanding of literacy without explaining it. Furthermore, we found that many subject areas frequently discussed in AI literacy literature, such as data visualization, are not specific to AI (e.g., Kandlhofer et al., 2016). However, many of these subject areas have an increased or shifted relevance due to the introduction of AI, for example, ethical literacy (e.g., I. Lee et al., 2021) (see Table 2.7). In pursuit of solidifying a specific understanding of what AI literacy constitutes, it is imperative for future research to use nuanced approaches that acknowledge different proficiency dimensions and draw on a subject area understanding that acknowledges AI specificities. Therefore, this direction seeks to pinpoint the AI-specific facets of AI literacy and distinguish it from other literacy concepts, such as digital or media literacy, more clearly in the future.

Future research could, for example, ask, "Which proficiency dimensions of AI literacy are associated with which subject areas most commonly?" Such a research inquiry would enhance our understanding of AI literacy as a holistic proficiency construct and add valuable insight to the conceptualization as well as how to teach different subject areas. On the other hand, future studies could further explore the differences between AI-specific and non-AI-specific subject areas of AI literacy. One could ask, "Which subject areas are essential to gain a specific understanding of AI for using it in the non-expert context?" or "In how far does AI literacy build on related literacy concepts, such as digital literacy?" Such inquiries could yield valuable information on the prerequisites for an AI-specific understanding. In other words, future research could explore what one needs to know about non-AI to comprehend AI appropriately.

Research Direction IV. Refine AI literacy needs for diverse AI user groups. Prior AI literacy research identified AI literacy needs (i.e., required AI literacy proficiency dimensions and subject areas) for different AI user groups, such as medical doctors (Charow et al., 2021) and journalists (Deuze & Beckett, 2022). However, there is a need for further refinement of the specific AI literacy needs of different AI user groups. Studies on individual AI user groups emerged in the constituting phase of AI literacy. As such, they partially draw on incomplete conceptualizations of AI literacy. Based on more comprehensive and AI-specific conceptualizations, we urge future research to refine our thinking on who needs which areas of AI literacy and to what specific depth. The necessary and optimal depth of each AI literacy area (see Table 2.5) will vary for each user group. Future research could aim to understand better the optimal depth of rather technical AI literacy areas, such as AI models, for adult lay users. One could ask, "Which technical AI model aspects help adult non-expert users in their AI interactions, and which excessive technicalities hinder overall comprehension?"

Furthermore, there are relevant AI user groups that have not yet been explored regarding their AI literacy needs (see Appendix 2.C, Table 2.11). Complementary to the questions posed in research direction I concerning learning methods for unexplored AI user groups, the AI literacy needs for these unexplored groups also need to be considered. Omitted but highly relevant user groups in the AI context include judges, bankers, or recruiters, among others (see Appendix 2.C, Table 2.11). For example, it is crucial to identify which AI literacy needs judges and policymakers have before considering how to convey them. As such, one could seek to answer, "Which AI literacy proficiency dimensions and areas are relevant for judges?"

2.5.1.3 Directions for the Effects of AI Literacy

Research Direction V. Explore the humanistic effects of AI literacy. When assessing the current research landscape concerning the effects of AI literacy, one notes a strong emphasis on instrumental effects, such as appropriate delegation (Pinski, Adam, & Benlian, 2023) or performance (Chiang & Yin, 2022). However, research urges to explore a socio-technical phenomenon like AI with both an instrumental and a humanistic lens (Sarker et al., 2019). Individual studies looked at highly relevant humanistic outcomes, such as the ability to discern gender bias (Melsión et al., 2021) or the ability to self-advocate against harmful AI (Register & Ko, 2020). However, there are many more humanistic outcomes that future research should explore. Specifically concerning a technology like AI, with the potential to adversely impact human life, we urge future research to explore more diverse effects of AI literacy. We need to understand better which humanistic goals can be achieved through AI literacy and where we need further measures, such as regulation. For instance, one could ask, "How does AI literacy impact the well-being of humans working in human-AI collaborations?"

In that vein, one could also aim to dissect the impact of individual AI literacy subject areas on such humanistic outcomes. A more granular view of the effects of specific AI literacy areas could then, in turn, inform improved user-specific AI literacy conceptualizations. One could hypothesize that technical knowledge about AI functionality takes discomfort about AI away by demystifying it. However, technical knowledge might also confuse unknowledgeable users more and thus amplify discomfort toward AI. As such, future research could investigate, "Which AI literacy subject areas have which effect on human well-being in human-AI collaborations?"

Research Direction VI. Consider moderating factors to contextualize AI literacy's effects. Research investigating the effects of AI literacy has so far predominantly focused on the direct effect of possessing or increasing AI literacy on different outcomes. Some studies seem to collectively confirm an underlying relationship, such as AI literacy's positive influence on appropriate delegation behavior (Pinski, Adam, & Benlian, 2023), appropriate reliance (Leichtmann et al., 2023), and appropriate trust (Chiang & Yin, 2022), which all support that AI literacy has positive effects for human-AI collaboration. However, other AI literacy effects are not that clear. For example, whereas Pinski, Haas, and Franz (2023) find that AI literacy leads to a more positive attitude toward AI, Tully et al. (2023) find that AI literacy decreases AI receptivity. One might argue that attitude toward AI and AI receptivity are related constructs, which poses the question of why the effects are opposed to each other. What might explain this puzzle are moderating factors that modify AI literacy's effect on affective outcomes, such as the type of AI or the setting in which the participants have been asked. Therefore, we call for future research to identify moderating factors that can increase our understanding of the effects of AI literacy. Also, the findings on AI usage continuance intentions (Pinski, Adam, & Benlian, 2023; Pinski, Haas, & Franz, 2023) and on performance in human-AI collaborations are mixed (Chiang & Yin, 2022;

Leichtmann et al., 2023), i.e., they do not point in the same direction. Therefore, future studies could ask, "How does the type of AI affect AI literacy's effect on human attitude and receptivity toward AI?"

Moreover, there is a general notion in the AI literacy literature that AI literacy is positive for humans. While most effects of AI literacy also seem to support this (see Table 2.8), there are scenarios imaginable where AI literacy might not be positive. For example, if one belongs to a minority suffering from different biases in the real world, some might perceive learning about technologies that reinforce these biases as not liberating but as increasing feelings of repression. As such, future research could also ask, "Which moderating factors contribute to AI literacy being positive for humans and which to it being negative?"

2.5.2 Contributions to Research and Practice

In this study, we conducted a systematic, scoping literature review to assess the research landscape on AI literacy for AI users with respect to the learning methods for AI literacy, the components of AI literacy, and the effects of AI literacy. Based on our review and assessment of the literature, this study makes the following contributions to AI literacy literature:

First, AI literacy as a research field emerged only recently. However, the field has matured significantly in recent years and produced a variety of new studies. Prior research often focused on the components of AI literacy (e.g., Long and Magerko, 2020). We depart from this approach and comprehensively summarize and structure the existing research along the three most discussed topics: learning methods, components, and effects of AI literacy. Thereby, we develop an overarching conceptual framework comprising additional detailed conceptualizations for each relevant AI literacy aspect. To our knowledge, no reviews regarding learning methods and the effects of AI literacy are available in the literature. As such, we extend the conceptual understanding of AI literacy by structuring the currently fragmented discourse.

Second, based on our comprehensive review, we contribute a research agenda to determine the most promising research opportunities for advancing AI literacy. Along the three core components of the presented framework, we deduce six concrete research directions.

Third, many studies focus on individual AI user groups, such as medical doctors (Charow et al., 2021) or teachers (Kim & Kwon, 2023). While important groups have been covered regarding some aspects, many relevant user groups have been omitted until now, and a comprehensive overview has been lacking. Our study contributes a comparative analysis of different AI user groups, shifting the discourse in a more user-group-sensitive direction. Thus, we ensure that studies focused on specific user groups can learn from each other, and we expose unexplored AI user groups.

Fourth, “AI” is an elusive term with different definitions that coexist in the literature (e.g., Berente et al., 2021; Duan et al., 2019; Rai et al., 2019). Much prior AI literacy research does not define the term AI before building AI literacy research on it. In contrast, recent IS research focusing on AI in general aims to specify the term AI more clearly by conceptualizing facets that distinguish AI from non-AI (Berente et al., 2021). We urge AI literacy research to follow suit to promote a more specific discourse. In our literature review, we applied the AI facets of Berente et al. (2021) to scrutinize our findings, in particular the components of AI literacy, regarding their AI specificity. Thus, we challenge undifferentiated thinking on what constitutes AI literacy and contribute a more specific viewpoint, untangling related literacy concepts, such as digital or data literacy, from AI literacy. Overall, one can observe that AI literacy embodies a shift in the human relationship to technology. Many aspects, such as ethics, have also been important for non-AI technology. However, these aspects gain relevance next to technology proficiency due to AI increasingly impacting more parts of human life to a greater extent. Applying this AI lens, we contribute to a more thorough understanding of what AI literacy refers to and how the construct relates to other technology literacies.

Fifth, concerning practice, this review also provides a reference for educators, policymakers, and business decision-makers, who must make critical decisions regarding the future standards of AI literacy in educational institutions, society, and business. For example, educators could leverage the overview of learning methods to assess if their current classes are utilizing the most suitable learning method. Policymakers can leverage the AI literacy component conceptualization to assess if their curricula are addressing all relevant parts of AI literacy. Lastly, business decision-makers can draw on the overview of known effects of AI literacy to better judge where and how to implement AI use cases and AI literacy education interventions in their firms.

2.5.3 Limitations

As with any study, our study comes with several limitations. First, we selected highly regarded databases within the information systems, human-computer interaction, and computer education research fields for our search, as practiced by other literature review studies from the discipline (e.g., Krath et al., 2021). However, our study is limited by the fact that we cannot include databases from all scientific disciplines. Other databases might have included further studies shedding light on AI literacy from the perspective of a different discipline. Second, our study explicitly focused on AI literacy for users and, hence, used the search terms “AI literacy” and “artificial intelligence literacy” and assessed the user focus via manual screening. By focusing on the term “literacy,” we aimed to capture studies explicitly referring to the holistic human proficiency construct of literacy. However, given that the field of AI literacy is still emerging and the term is not yet commonly defined, other studies might have used other terms to describe the same phenomena. As such, our study is potentially limited by the employed search terms. Including other terms might have yielded different results. Third, we structured the identified literature using established conceptualizations, which we deem purposeful for the respective research stream of AI literacy (e.g., formal vs. informal learning methods). However, we note that this way of structuring the literature does not represent the only way that the literature can be structured. Other concepts or hierarchies of the structuring dimensions might yield AI literacy conceptualization with different emphases.

2.6 Conclusion

This study examined the current landscape of AI literacy for users, encompassing learning methods, components, and effects. Through a scoping literature review, it developed a comprehensive account of AI user groups, structured different types of learning methods, identified the different proficiency dimensions and subject areas ascribed to AI literacy, and organized the effect of AI literacy on AI users. Furthermore, we scrutinized the different aspects regarding their AI specificity, using AI’s facets of inscrutability, learning, and autonomy. This study lays the foundation for tailored educational initiatives, informed policymaking, and strategic business decisions as it refines our understanding of AI literacy’s specificity. Furthermore, we deducted a research agenda, including six future research directions. As AI’s influence deepens, equipping individuals with the ability to navigate AI’s complexities emerges as a pivotal undertaking for harnessing AI’s transformative potential and ensuring efficient and ethical human-AI collaborations.

2.7 Appendix of Chapter 2

2.7.1 Appendix 2.A: Coding Process

Beyond the metadata of the results (e.g., year of publication, research method), two independent coders coded in a first iteration the AI user groups, the AI literacy research avenues, and different themes they identified within the research avenues (Table 2.11). After they completed the open coding, they refined the themes within each research avenue via discussion. In a second iteration, the coders coded the papers again based on the discussion results, concretizing the detailed coding scheme within each research direction. After that, they discussed the results and discrepancies again until a consensus was achieved. In coding the AI literacy research avenues (i.e., learning methods for AI literacy, components of AI literacy, effects of AI literacy), we considered the study's contributions holistically without focusing on particular keywords. The research avenues do not mutually exclude each other, i.e., we allowed the assignment of studies to multiple research avenues if they contributed significantly to both. We depict the coding scheme in Table 2.10.

Coding category	Coding dimension	Coding values
Metadata	Year of publication	Year [2016-2023]
	Paper type	Conference proceedings, journal article, dissertation
	Research method	Design science research, literature review, experiment, discussion, interview study, case study, observational study, scale development, survey, secondary data analysis, commentary, taxonomy development, conceptual analysis, mixed methods
	Research discipline	Computer education, HCI, information systems, management, medicine, media studies, computer science
User groups	User context	Expert domain, non-expert domain
	Expert domain	NAICS codes [10-99]
	Non-expert domain	Student, Adult
Research avenues	AI literacy research avenue	Learning methods for AI literacy, components of AI literacy, effects of AI literacy
Learning methods for AI literacy	Type of learning method	Formal learning methods, informal learning methods
	Subtype of formal learning methods	Lecture-based, exercise-based (traditional exercises, interactive exercises, artifact-based (interaction, construction)
	Subtype of informal learning methods	Community-based, self-directed exercise-based, self-directed artifact-based (interaction, construction)
Components of AI literacy	Subject areas	See Tables 2.5, 2.6, and 2.7 for areas and subareas
Effects of AI Literacy	Nature of effect	Humanistic, instrumental
	Human learning outcome type	Affective, behavioral, cognitive

Table 2.10: *Coding Scheme*

2.7.2 Appendix 2.B: Selection Summary

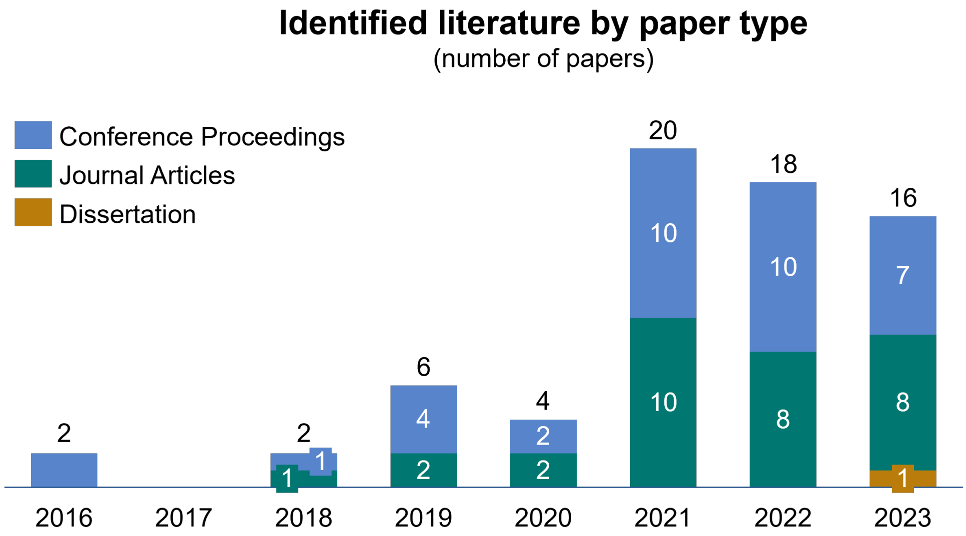

Figure 2.6: *Identified Literature by Paper Type and Year of Publication*

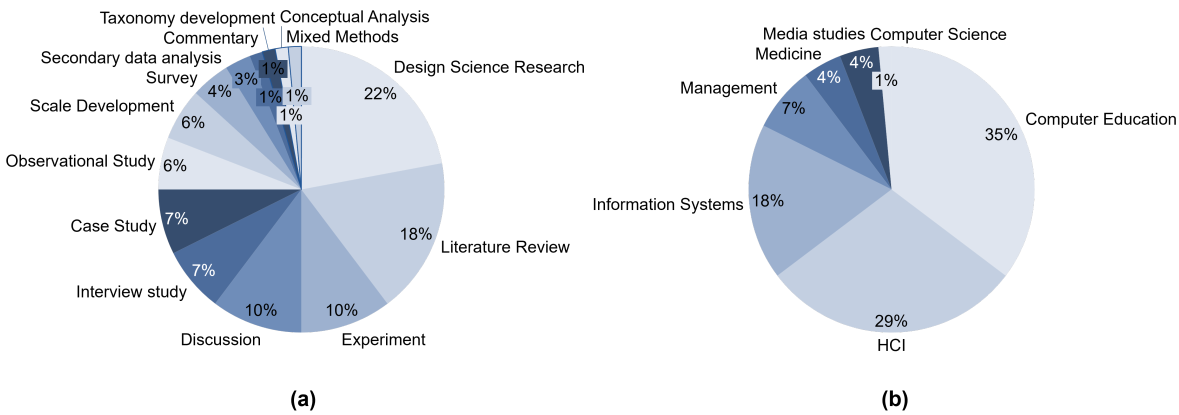

Figure 2.7: *Identified Literature by Research Method (a) and Research Discipline (b)*

2.7.3 Appendix 2.C: User Group Framework for Expert Context

Domain	**Eco. Activity NAICS code**	**Exemplary AI user groups**	**Sources**
Agriculture, Forestry, Fishing, Hunting	11	Farmers, Fishers	*Not covered yet*
Mining, Quarrying, Oil and Gas Extraction; Utilities; Construction	21-23	Construction workers, Geologists	Maitz et al. (2022)
Manufacturing	31-33	Engineers, Factory staff	Pillay et al. (2018)
Trade [Wholesale & Retail]	42-45	Sales agent, Retailer	*Not covered yet*
Transportation and Warehousing	48-49	Warehouse workers, Taxi drivers	*Not covered yet*
Information	51	News publisher, Librarians	Cox and Mazumdar (2022)
Finance and Insurance	52	Bankers, Actuaries	*Not covered yet*
Real Estate, Rental, Leasing	53	Brokers, Leasing agents	*Not covered yet*
Professional, Scientific, Technical Services	54	Consultants, Scientists, Accountants	*Not covered yet*
Management of Companies and Enterprises	55	Executives, Middle management	Jorzik et al. (2023), Pinski, Hofmann, and Benlian (2023), J. Yang et al. (2021)
Administrative, Support, Waste Management, Remediation Services	56	Recruiters, Facility managers	*Not covered yet*
Educational Services	61	Teachers, Professors, Counselors	Kim and Kwon (2023)
Healthcare and Social Assistance	62	Medical doctors, Nurses, Social care providers	Charow et al. (2021), Jussupow et al. (2021)
Arts, Entertainment, Recreation	71	Journalists, Screenplay writers	Deuze and Beckett (2022)
Accommodation and Food Services	72	Cooks, Hoteliers	*Not covered yet*
Public Administration	92	Policymakers, Law enforcers, Judges	*Not covered yet*

Table 2.11: *AI User Group Framework for Expert Context: Refined Including Future Research*

3 Measurement Development

Title:	AI Literacy - Towards Measuring Human Competency in Artificial Intelligence
Authors:	Marc Pinski, Technische Universität Darmstadt, Germany Alexander Benlian, Technische Universität Darmstadt, Germany
Published in:	Proceedings of the 56th Hawaii International Conference on System Sciences. January 3-6, Lahaina, USA.
Available at:	www.hdl.handle.net/10125/102649

Abstract

Artificial intelligence (AI) has gained significant traction in information systems (IS) research in recent years. While past studies have identified many effects of AI technology on human-AI collaborations, there is a paucity in IS literature on the competencies of humans that affect this relationship. In this study, we set out to develop a measurement instrument (scale) for general AI literacy, that is, humans' socio-technical competencies regarding AI. We conducted a systematic literature review followed by five expert interviews to define and conceptualize the construct of general AI literacy and to generate an initial set of items. Furthermore, we performed two rounds of card sorting with six and five judges and a pre-test study with 50 participants to evaluate the developed scale. The validated measurement instrument contains five dimensions and 13 items. We provide empirical support for the measurement model and conclude with future research directions.

Keywords: Artificial intelligence, AI competencies, AI skills, human-AI interaction, future of work

3.1 Introduction

Artificial intelligence (AI) and its impact on individual humans, their organizations, and their work have gained enormous traction within information systems (IS) research in recent years (Benbya et al., 2021; Berente et al., 2021; Jain et al., 2021). AI competence has risen to a key skill for humans with increasing importance for future work, whereas research increasingly calls for ways to improve AI competencies (Tarafdar et al., 2019). While IS research has produced an abundance of studies and frameworks of technical AI features to improve human-AI collaboration (Fügener et al., 2021b), hitherto, there are no mature conceptualizations and instruments available to measure general AI competence. While the impact of technical features on the success of human-AI collaborations is apparent, human socio-technical competence in AI drives it just as much (W. Cai et al., 2022). Academics did conceptualize and set up non-AI-specific measurement instruments for human IS competencies before AI's ascent (Bassellier et al., 2003). However, these lose their applicability when AI is involved since core assumptions of these IS frameworks are invalidated by AI (Schuetz & Venkatesh, 2020). While there are first conceptualizations to measure AI literacy in IS-adjunct fields (e.g., computer education B. Wang et al., 2022), these are focused on specific settings, such as humans in the role of users of AI applications. While this approach enables the measurement of highly specific aspects of AI literacy, it cannot be applied across different roles, for example, to compare different departments of a firm, such as R&D (e.g., developers of an AI tool) and sales (e.g., users of an AI tool). Assessing how the AI literacy of different roles compares to each other can yield valuable insights into the impact of AI literacy. A general scale independent of the human role is, to the best of our knowledge, still missing in core IS literature. Researchers have called for such a general AI competence construct in this still underexplored field to identify and measure key competencies for the future work with AI (Tarafdar et al., 2022).

We aim to fill this gap by defining and conceptualizing general AI literacy and by developing an instrument to measure the level of humans' general AI literacy. Therefore, we specify AI literacy as humans' socio-technical competence consisting of knowledge and experience, which are both distinct competency types that collectively constitute AI literacy. We draw on recent AI theorizing (Baird & Maruping, 2021; Berente et al., 2021; Schuetz & Venkatesh, 2020) and apply it to established design principles of human IS competence conceptualizations (Bassellier et al., 2003, 2015) to develop our measurement instrument.

We contribute to research and practice in four ways: First, we extend AI and human IS competence literature by specifying the competencies necessary for human-AI collaboration and establishing a connection between the IS research fields. Second, we contribute a measurement instrument that can be leveraged academically to investigate further relationships in the future of human work with AI or to enhance our understanding of AI acceptance. Third, the developed scale can be leveraged by practitioners, such as firms that can use the dimensions to analyze AI competencies of existing job roles or to determine AI skill requirements for new job roles. Humans working with AI can use the structure to better understand their future roles, assess AI task appropriateness, or develop AI-related ethical awareness. Educational institutions can leverage it to assess their AI curricula. Fourth, we leverage the AI literacy construct to structure future research.

In the following, subsection 3.2 introduces the conceptual foundations of human IS competencies and AI. While subsection 3.3 describes our research design and results, subsection 3.4 discusses contributions, and subsection 3.5 examines limitations and future research directions.

3.2 Conceptual Foundations

3.2.1 Human IS Competencies

Human competencies have been established as a core IS research field with a major influence on IS-related interactions of individuals, organizations, and society (Wiesche et al., 2020). Since the IS literature is not fully consistent in its usage of the term "competencies" (Chakravarty et al., 2013), we define competencies as human knowledge and experience, as opposed to concepts that include further organizational resources, such as information technology (IT) hardware assets (Sambamurthy et al., 2003). Within the field of human IS competencies, different studies have structured the relevant competencies and investigated their impact.

Looking at the conceptualized structures of human IS competencies, the literature acknowledged that relevant human IS competencies include not only technical competencies but also social competencies, such as business (Bassellier & Benbasat, 2004) or management competencies (Roepke et al., 2000). Thereby, competencies have been structured consistently in line with the socio-technical perspective which emphasizes the importance of interaction between the competence sets (Sarker et al., 2019). Beyond the content structuring of human IS competencies, research further agrees that human IS competencies can be divided qualitatively into "explicit knowledge," which can be taught, read, and explained, and "tacit knowledge," which is acquired by experience (Bassellier et al., 2015). Both knowledge forms have been shown to affect IS outcomes, such as performance, and need to be considered in interaction (Bassellier & Benbasat, 2004; Bassellier et al., 2003).

Furthermore, research has identified manifold effects of human IS competencies that exemplify the impact of the human component in IS (Chakravarty et al., 2013). To date, these studies predominantly focus on instrumental outcomes for the organization, such as performance (Croteau & Raymond, 2004) or innovativeness (Tarafdar & Gordon, 2007). Contrary, on the side of humanistic outcomes, such as the well-being of IT professionals, research did, to the best of our knowledge, not identify key relationships to IS competencies yet. Especially when moving from general IT to more immersive AI technology, a thorough understanding also of the effects on humanistic outcomes becomes more important.

3.2.2 Emerging Theory of AI and AI Literacy

After a thorough evaluation of the literature on IS competencies, one might argue that it seems to be a fairly explored field of IS research. However, when assessing literature on emergent theorizing of AI, it becomes imperative to revise also our theories and knowledge on competencies regarding technology subsumed under the term, which differ qualitatively from prior non-AI technology (Berente et al., 2021).

While academics have defined and conceptualized AI from many angles, Berente et al. (2021) provide a concise view that distinguishes AI from non-AI technology by conceptualizing three unique facets of AI: *autonomy*, *learning*, and *inscrutability*. These three facets invalidate core assumptions that IS theory was built on for decades (Baird & Maruping, 2021; Schuetz & Venkatesh, 2020; Tarafdar et al., 2022). Schuetz and Venkatesh (2020) identified five broken assumptions and evaluated how they would need to be revised to reflect the changes triggered by AI (Table 3.1). These identified AI facets and revised IS assumptions are the basis to evaluate how AI impacts our understanding of human IS competence.

Humans have always used technology, while the IT artifact had the passive role of a tool. With AI, artifacts are more *autonomous* and can assume an agentic role with their own goals (Baird & Maruping, 2021). This capacity enables AI artifacts to delegate tasks to humans, which makes their relationship bilateral (#1, Table 3.1)

#	**Broken IS assumption**	**Revised IS assumption**
1	Humans are users	Bilateral human-AI relationships
2	The developer defines the inputs	AI is aware of the environment
3	IT artifact use leads to consistent outcomes	AI can be functionally inconsistent
4	The way the tool derives its outcomes is comprehensible and can be verified	AI can be functionally not transparent
5	There is an artificial interface	Humans can be unaware of their AI use

Table 3.1: *Broken and Revised IS Assumptions by Schuetz and Venkatesh (2020)*

(Fügener et al., 2021a). Furthermore, AI artifacts are more autonomous because they are aware of their environment and process new types of input. Voice assistants, such as Alexa, listen continuously and process unstructured data like speech, which have not been specified by a developer in advance (#2, Table 3.1). Contrary to non-AI artifacts, which produce consistent and deterministic outcomes, AI artifacts *learn*, which implies functional inconsistency. The artifacts can incorporate feedback from their produced output and adjust their inner workings accordingly (#3, Table 3.1). Additionally, AI is often not transparent to its users and even developers. Neural networks are *inscrutable* because their enormous complexity makes it impossible for humans to understand how they derive their outcomes (#4, Table 3.1). Finally, AI artifacts differ from non-AI artifacts because they do not always have an artificial interface that reveals to the user that they interact with technology. For example, human voice assistants are so close to the actual human voice that they can interact with humans without them noticing (#5, Table 3.1) (Y. Wang et al., 2017).

How these revised assumptions impact IS theory has been explored, for example, with regards to the ways humans and AI collaborate (Jain et al., 2021) or organizations function (Benbya et al., 2021). Both underline the human factor and, hence, also the role human IS competencies will play in AI theorizing. However, we have to assert that hitherto, the AI study coverage in the IS literature is highly skewed towards the technical end of the socio-technical continuum, which holds especially for human competencies in AI (Sarker et al., 2019). Nevertheless, there are initial conceptualizations and definitions of AI literacy. Long and Magerko (2020) collocate 17 human competencies and 15 design considerations structured with five key questions: “What is AI?,” “What can AI do?,” “How does AI work?,” “How should AI be used?,” and “How do people perceive AI?.” Heyder and Posegga (2021) draw on this work and structure the competencies into three conceptual blocks: Functional AI literacy, critical AI literacy, and sociocultural AI literacy. While this structure segments competencies by their content, Ng et al. (2021) structure human competencies by their skill type into three categories inspired

AI skill type	Definition
Know and understand AI	Know the basic functions of AI and how to use AI applications
Use and apply AI	Applying AI knowledge, concepts, and applications in different scenarios
Evaluate and create AI	Higher-order thinking skills (e.g., evaluate, appraise, predict, design) with AI applications
AI ethics	Human-centered considerations (e.g., fairness, accountability, transparency, ethics, safety)

Table 3.2: *AI Literacy Skill Type Definitions by Ng et al. (2021)*

by Bloom's taxonomy for competencies (know & understand, use & apply, evaluate & create) with the addition of AI ethics (Krathwohl, 2010). They synthesized a definition for each category based on a literature review (Table 3.2).

3.3 Research Design: Towards a Scale for Measuring General AI Literacy

The key objective and contribution of this study is the development and evaluation of a scale to measure the level of general AI literacy. IS research has established systematic and rigorous approaches to develop such a scale (MacKenzie et al., 2011). Adhering to these guidelines, we set up a four-step research design to develop a measurement instrument (Figure 3.1).

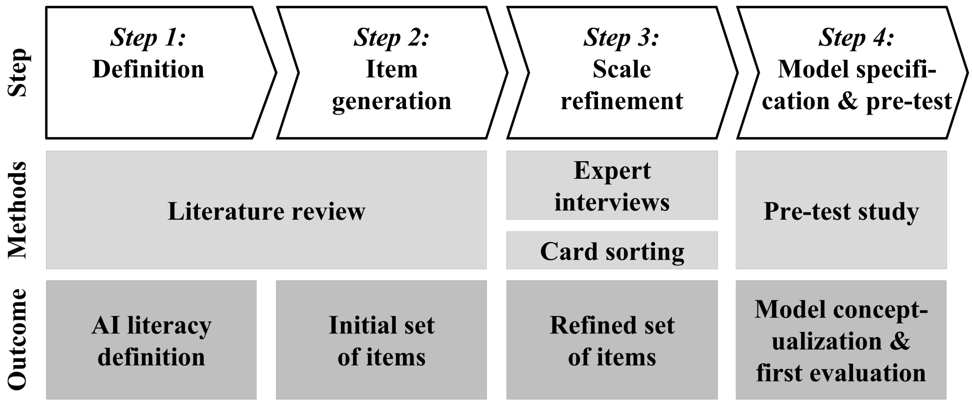

Figure 3.1: *Research Design*

Initially, we defined general AI literacy to set up the foundation for our focal measurement construct by conducting a systematic literature review on key themes of AI and human IS competence (step 1). Then, we generated items based on our review for each of the conceptualized dimensions of general AI literacy (step 2). Thereafter, we refined the initial scale by interviewing experts and conducting a card-sorting exercise to assess content validity (step 3). Finally, we specified the formal measurement model and conducted a pre-test study as a first evaluation (step 4).

The four outlined steps are in line with MacKenzie et al.'s (2011) steps 1-5 of scale development. In the following, we elaborate on each step of the scale development process.

3.3.1 Definition of the Focal Measurement Construct (Step 1)

We initiated the scale development process by systematically reviewing the literature. To ensure a diligent literature review, we followed established guidelines practiced in IS research (Webster & Watson, 2002). We combined a direct search specifically on "AI literacy" with two supplementary searches on the more general fields of "AI" and "IS competencies" (Appendix 3.B). For the direct search, we used a broad set of 18 IS journals and conferences to cover emergent research, while we focused on the Senior Scholars' Basket of IS Journals for the supplementary searches to only include theorizing with a certain maturity. The search resulted in 172 articles, which were screened by reading titles and abstracts. After pre-selection followed by deep reading, 21 studies remained relevant for the development of the focal measurement construct. The search was supplemented with relevant papers from adjacent fields identified via forward and backward reference search in the identified papers.

Subsection 3.2 gave an overview of the conceptual foundations from the underlying theories within human IS competencies and AI identified with the process described above. Furthermore, we assessed existing AI literacy definitions (Table 3.2, Ng et al., 2021) and conceptualizations (Heyder & Posegga, 2021; Long & Magerko, 2020; B. Wang et al., 2022). In the following, we highlight how the presented research is synthesized into a definition to guide the scale development process of general AI literacy.

Drawing on the literature, we first define the goal of our scale. We aim to establish a scale enabling us to measure AI competence in a general and inclusive way – an approach also followed by other IS constructs (Malhotra et al., 2004). In this context, we refer to AI in the sense of cognitive computing systems (Schuetz & Venkatesh, 2020). To avoid losing practical value or usability, the scale should neither be focused on a specific instance or design of AI, nor a specific job role. This will allow for broad practical applicability, for example, among firms when assessing their organization. The primary target audience shall be all employees in AI-related positions (direct & indirect). Next, we discuss how three synthesized themes (I-III) from the literature inform our adopted definition, which concludes the first step.

(I) Core theme of different competency conceptualizations is the *socio-technical perspective* (Bassellier et al., 2015; Sarker et al., 2019). When defining general AI literacy for a scale, we follow this perspective, which implies that the dimensions and items should reflect both, competencies in AI technology as well as competencies in human factors involved in AI. Many AI competencies rely on a high interaction of social and technical aspects. Therefore, we decided to incorporate the theme in the definition by referring to competencies jointly rather than splitting social and technical competencies on the first level.

(II) *The segmentation of competencies into explicit knowledge and tacit knowledge* is a common split in competence research and has already been applied in non-AI competence conceptualizations (Bassellier et al., 2015). Hence, we incorporate it in our AI literacy definition to guide the scale development accordingly. For further clarity, we distinguish our terminology into knowledge (explicit literacy) and experience (tacit literacy).

(III) So far, the themes were in line with IS competence theorizing. However, the theme of *broken IS assumptions* demands to accommodate AI's particularities. The first and the fifth revised assumptions state that there is a *bilateral relationship between humans and AI* and that for their interaction, there is *no artificial interface* necessary anymore, which underlines the socio-technical perspective (Table 3.1). Therefore, general AI literacy needs to comprise competencies regarding technology subsumed under the term AI (agentic AI artifacts/actors), such as how AI is distinct from non-AI or where AI can be used. But it also needs to include competencies regarding the human actors involved in the human-AI collaboration, such as tasks where humans are superior to AI or which humans are involved in human-AI collaboration. Furthermore, humans need new competencies on how to recognize AI and what implications it has that humans can now be unaware of their AI interaction (Long & Magerko, 2020). The second, third, and fourth revised assumptions translate into the *steps of how AI handles input, processes the received information, and produces output* (Table 3.1). For each step, humans need competencies on how to handle what has fundamentally changed compared to non-AI. For example, humans need to know that AI perceives input differently and that input has different effects on an AI artifact compared to a non-AI artifact. Furthermore, humans must develop competencies to judge what it means for an AI application in a certain field (e.g., medicine or business) to not be functionally transparent (e.g., legal and ethical implications or effects on humans interacting with AI). When an AI artifact has derived an outcome, humans now need new competencies on how to handle and interpret it.

Considering the introduced definitions (subsection 3.2) as well as the identified themes (I – III) of the AI and human IS competence literature, we define for the purpose of developing a measurement instrument:

> *General AI literacy is humans' socio-technical competence consisting of knowledge regarding human and AI actors in human-AI interaction, knowledge of the AI process steps, that is input, processing, and output, and experience in AI interaction.*

3.3.2 Item Generation (Step 2)

Based on the literature review described in step 1 and the subsequently adopted definition of general AI literacy, we generated an initial set of items. We considered the item style of previous competence conceptualizations when setting up the items (Bassellier et al., 2003).

In our scale development for general AI literacy, our focus was to measure the human perception of competencies. AI research has shown that metaknowledge, that is, one's knowledge about one's knowledge, is a key determinant for the success of human-AI collaboration (Fügener et al., 2021a). While being aware of the drawbacks of a subjective scale, we considered perception, which measures the assessment of the own knowledge as a first step towards the measurement of general AI literacy most relevant. Research has further specifically called for better assessment of metaknowledge, which our scale contributes to (Fügener et al., 2021a). Additionally, a self-assessment serves the purpose of an inclusive scale that is neither focused on users nor developers as both assess the perception of their literacy for their role in the general construct dimensions.

We aimed to set up the items at the intersections of the three introduced themes "socio-technical," "explicit/tacit," and "revised IS assumptions." For example, each revised assumption (Table 3.1) was targeted to be itemized regarding its social and technical implications. Overall, we aimed to start the process with a list balanced around the themes. The initial list comprised 46 items structured along six dimensions (AI & human actors, AI interface, AI input, AI processing, AI output, AI experience), which entered the refinement process.

#	Field	Expert (Order of interview execution)
1	AI practitioner	Senior director at international strategy consultancy
2	AI/IS academic	Senior lecturer & researcher
3	AI/IS academic	Post-doctoral researcher
4	IS practitioner	Head of IT department in an established enterprise
5	AI practitioner	Founder of AI start-up

Table 3.3: *List of Interviewed Experts*

3.3.3 Scale Refinement (Step 3)

In step 3, we used two refinement methods to assess content validity and scale design: First, a round of expert interviews was conducted to incorporate different viewpoints on AI. Second, two rounds of card sorting were performed to assess whether the items were correctly associated with the dimensions.

The combination of systematic literature review and expert interviews is recommended by the literature and assumed to identify a set of potential items with high validity (G. C. Moore & Benbasat, 1991). Therefore, we conducted partially open-ended expert interviews to identify further dimensions and aspects of general AI literacy as well as gather feedback on the initial set of items. Given that we chose a general approach to AI literacy, we aimed for AI and IS experts with different backgrounds and expertise. In total, we interviewed five experts. Two experts had an academic background, and three were practitioners (Table 3.3).

Both interviewed academics had an AI/IS background with publications in highly ranked journals. The practitioners were selected from a consultancy, an established enterprise, and an AI startup to obtain a holistic view of AI in practice. Four interviews were conducted online, and one was face-to-face. Initially, experts were asked in an open-ended manner to describe their understanding of AI literacy and how they would conceptualize the construct. After we elicited the expert's views on AI literacy without prior cues through open-ended questions, we showed the expert our conceptualization and items and applied think-aloud techniques for further input. Leveraging open-ended and think-aloud techniques together gave us perspectives we had not been able to see before.

A key result of the expert interviews was that all experts intuitively confirmed the importance of the socio-technical perspective, as well as the explicit and tacit knowledge components. Also, from the six originally entered dimensions that were derived from the literature, the three dimensions aimed at an understanding of the

Category	Construct dimension
AI actor knowledge (AK)	**AI technology knowledge (TK)** *Definition: Knowledge of what makes AI technology distinct and the role of AI in human-AI collaboration and interaction*
	Human actors in AI knowledge (HK) *Definition: Knowledge of the role of human actors in human-AI collaboration and interaction*
AI steps knowledge(SK)	**AI input knowledge (IK)** *Definition: Knowledge of what AI input is and how humans should use it*
	AI processing knowledge (PK) *Definition: Knowledge of how AI processes information and what effects it has on humans*
	AI output knowledge (OK) *Definition: Knowledge of what AI output is and how humans should use it*
AI experience (EX)	**AI usage experience (UE)** *Definition: Experience in interacting with AI*
	AI design experience (DE) *Definition: Experience in designing and setting up AI*

Table 3.4: *General AI Literacy Construct Dimensions*

AI steps (input, processing, output) could be validated as meaningful. However, the dimensions "AI & human actors" and "AI interface" which were also derived from the revised IS assumptions by Schuetz and Venkatesh (2020) did not intuitively resonate with a majority of the experts. Following suggestions from the experts for more clarity, we restructured the two dimensions into "AI technology" and "Human actors in AI." Furthermore, it was recommended to separate the experience dimension into usage and design, which we adopted. Subsequently, we restructured the construct into seven dimensions (Table 3.4). The dimensions are grouped into three categories: AI actor knowledge (explicit literacy), AI steps knowledge (explicit literacy), and AI experience (tacit literacy). Finally, we reworded the item set based on the feedback elicited via the think-aloud technique from the experts. The refined items then entered the card sorting process.

Next, we performed two rounds of card sorting to ensure further content validity of the items. The method is considered appropriate to validate that items are individually representative of their dimension and that items within a dimension are collectively representative of the entire content of that dimension (MacKenzie et al., 2011). We selected the item placement ratio ("hit-ratio") (G. C. Moore & Benbasat, 1991) and Cohen's kappa (Cohen, 2016) as two established measures for the inter-rater agreement to evaluate the card sorting results. Judges for the card sorting exercise have been acquired through the survey platform Prolific and pre-filtered for frequent technology use at work (> 2 times a week). The judges were first instructed about the exercise and provided with the definitions of each dimension (Table 3.4). Thereafter, they were asked to allocate each item to exactly one of the seven dimensions, while additionally, the option to choose "n/a" was given. The items were shown in a randomized order, and several attention checks were implemented to ensure that the judges exerted appropriate effort. After excluding judges who failed the attention checks, six judges remained in the first-round exercise and five judges in the second-round exercise.

In the first round, the judges were asked to assign each item from the initial set of 46 items, which was the outcome of the expert interviews phase. The average hit-ratio of all dimensions was .52 with a Cohen's kappa of .27, both indicating a need for further refinement. As a result, items with the lowest hit ratios were dropped, and the wording of the remaining items was adjusted. A set of 25 items was retained for the next iteration.

The second round of card sorting was conducted in the same setup but with a completely new set of judges. The average hit-ratio improved significantly to .86 which we deemed sufficient following prior research that considers .80 as the average hit-ratio threshold value (G. C. Moore & Benbasat, 1991). The hit-ratios in each dimension were also at individually appropriate levels, ranging from .70 to 1.00 (Table 3.5). Furthermore, Cohen's kappa improved to .74, which lies above the commonly used threshold of .70 (Boudreau et al., 2001). The range of all inter-rater kappa statistics was .62 to .89, which indicated strong inter-rater agreement (Landis & Koch, 1977). Based on the improved inter-rater agreement measures, we considered the content validity of the refined item set appropriate.

3.3.4 Model Specification & Pre-test (Step 4)

In step 4, we first formally specified the measurement model and then conducted a pre-test study in line with established guidelines (MacKenzie et al., 2011). Subsequently, we assessed the measurement model of the general AI literacy construct by analyzing discriminant validity, convergent validity, internal consistency, multicollinearity, and item loadings (Fornell & Larcker, 1981). According to MacKenzie et al. (2011), the formal specification should capture the expected relationships between the items, construct dimensions, and focal construct. These relationships can be described either as formative ("defining characteristics of the construct") or reflective ("manifestations of the construct"). Based on the initial structure (Table 3.4), we define our construct

			Theoretical dimensions							
			AK		SK			EX		-
			TK	HK	IK	PK	OK	UE	DE	N/A
Allocated dimensions	AK	TK	14	2	0	0	0	1	0	0
		HK	1	22	2	0	1	0	0	0
	SK	IK	0	0	18	0	0	0	0	0
		PK	0	0	0	17	0	0	0	0
		OK	1	0	0	1	19	0	0	0
	EX	UE	2	1	0	0	0	7	0	0
		DE	1	0	0	1	0	1	10	0
	-	N/A	1	0	0	1	0	1	0	0
Item placement			20	25	20	20	20	10	10	0
Hit-ratio			.70	.88	.90	.85	.95	.70	1.00	-

Table 3.5: *Results of Second-round Card Sorting*

as a multidimensional construct that is commonly found in IS literature (Croitor & Benlian, 2019). We specify the items as reflective of their dimensions, such as "AI technology knowledge," because the dimensions exist at a deeper, more embedded level than what the items describe. Furthermore, it seems likely that a change in one item would affect other items in the same dimensions. The dimensions themselves are specified as formative of general AI literacy because it seems plausible that, for example, "Human actors in AI" and "AI technology" knowledge both increase AI literacy, but a change in the "Human actors in AI" dimension does not necessarily cause a change in "AI technology" dimension.

After our specification, we conducted a pre-test study with 50 participants who were asked to state their agreement with the dimension items and overall general construct items on a 7-point Likert scale (strongly disagree to strongly agree). Participants were acquired through the survey platform Prolific with a pre-screening for high technology usage (greater than daily) and programming skills to ensure a sample with sufficiently discriminant validity. Several attention checks were applied to ensure that the participants carefully assessed each item. The participants were, on average, 32.8 years old; the gender distribution was 36% female, 62% male, and 2% other; and the highest educational achievement was a university degree for 66%, a high school diploma for 32%, and an apprenticeship for 2%. Taking into account that our construct is defined to measure general AI literacy, we considered the sample appropriate. While the sample size is at the lower recommended end, we considered it sufficient for an internal measurements pre-test.

Our *initial model* with seven dimensions showed an overall good fit (R^2 =

.81), however, we discovered that the dimensions within AI steps knowledge (input, processing, output) suffered multicollinearity issues (Variance Inflation Factors (VIF) > 5.00) which we interpret as a too granular approach in a technology-driven dimension for a construct with a general approach.

Subsequently, we adjusted and simplified our measurement model by merging the "AI steps knowledge" dimensions (IK, PK, OK) into one dimension (AI steps knowledge, SK), which has been conceptualized as a category in the previous subsection already. We excluded several items and retained one item from each of the step dimensions (IK, PK, OK) for the new unified step dimension (SK). Furthermore, we optimized the item selection for consistency in the other dimensions, leaving a final set of 13 items for our *adjusted model*.

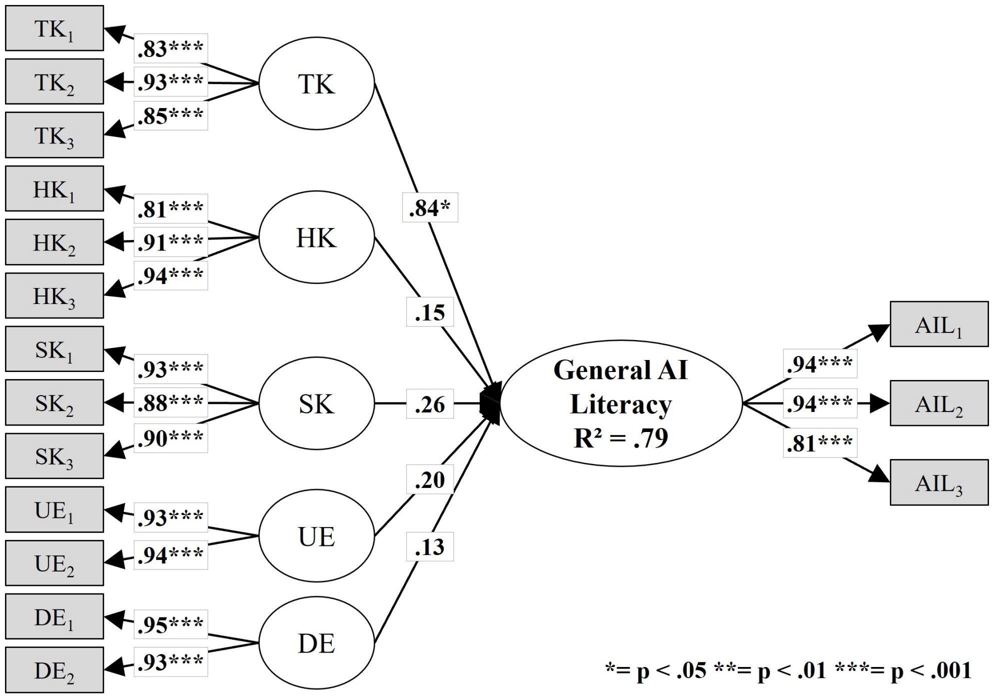

Figure 3.2: *Path Analysis of Structural Equation Model (Adjusted Model)*

The adjusted model (Figure 3.2) also yielded an appropriate fit (R^2 = .79) but additionally satisfied all recommended model tests (Table 3.6) (Fornell & Larcker, 1981): The VIFs were below 5.00 for all dimensions ensuring no multicollinearity problems (Gefen et al., 2011). Furthermore, all dimensions satisfied the Fornell-Larcker criterion (square root of average variance extracted greater than all correlations to other latent variables), indicating sufficient discriminant validity. Cronbach's alpha (CA) was greater than .84 for all dimensions which lies above the commonly accepted threshold of .70 for

		AK		SK	EX		AIL	CR	CA	VIF
		TK	HK	SK	UE	DE	-			
AK	TK	**.87**						.91	.84	4.47
	HK	.75	**.89**					.92	.87	2.26
SK	SK	.77	.58	**.90**				.93	.88	4.51
EX	UE	.57	.38	.45	**.94**			.94	.86	1.50
	DE	.47	.34	.74	.32	**.94**		.94	.87	2.34
AIL	-	.82	.67	.79	.61	.59	**.93**	.95	.92	-

Table 3.6: *Correlation Matrix (square root of average variance extracted in bold), Composite Reliability (CR), Cronbach's Alpha (CA), Variance Inflation Factors (VIF)*

internal consistency. Finally, item loadings were all above the recommended threshold of .70 (Figure 3.2) at a significance level of $p < .001$, and the composite reliability (CR) is above .91 for all dimensions which exceeds the threshold of .80. Overall, the results indicate strong empirical support for the adjusted measurement model. Since the initial model satisfied all tests mentioned, except multicollinearity, indicating some empirical support, we include for future reference both in Appendix 3.A (Initial model – 25 items; adjusted model – subset of 13 items)

While the adjusted model explained 79% of the variance of the general AI literacy construct, only the dimension "AI technology knowledge" ($\beta = .34$) had a strong and significant ($p < .05$) effect on general AI literacy. Despite the low path coefficients of the other dimensions, we decided to retain them in the model, as practiced in other IS construct developments (Croitor & Benlian, 2019), because they add key content for the focal construct, the importance of the dimensions might differ in different contexts of AI literacy, and the dimensions do not have collinearity issues (Table 3.6).

3.4 Contributions to Research and Practice

Our conceptualization and measurement instrument of general AI literacy contribute to research and practice in four ways. First, we provide an extension and specification of existing competency conceptualizations (Bassellier et al., 2003) with regards to AI (Schuetz & Venkatesh, 2020). Our developed construct picks up established aspects of IS competency literature and applies AI specificities to them, yielding an empirically tested instrument to measure the level of general AI literacy. By bridging the human IS competence and AI research streams, our instrument also extends the AI literature in IS through structuring human AI competencies. Second, we contribute an instrument to IS research that enables further exploration of the relationships of AI literacy to

Dimension	Potential research questions
AI technology knowledge (TK)	*Content:* How does AI technology knowledge in different organizational roles (e.g., developer and product manager) impact the effectiveness of their cooperation? *Scale:* Knowledge on which AI features is especially decisive to measure AI technology knowledge?
Human actors in AI knowledge (HK)	*Content:* How does the knowledge of specific human advantages and disadvantages over AI impact human-AI collaboration? *Scale:* What are the key human actors that should be represented in the general AI literacy of a human?
AI steps knowledge (SK)	*Content:* Is knowledge of AI input and AI output interpretation sufficient to enable humans to handle ethical dilemmas with AI? *Scale:* Which AI step (input, processing, output) has the highest impact on general AI literacy?
AI usage experience (UE)	*Content:* In which organizational roles is AI usage experience most needed and more important than explicit knowledge? *Scale:* Which specific AI experiences can be itemized in a scale and describe usage experience most appropriately?
AI design experience (DE)	*Content:* Is high-level AI design experience (e.g., simple visual modeling) beneficial for managers in their role (e.g., enhancing communication with technical employees?) *Scale:* Which specific AI experiences can be itemized in a scale and describe design experience most appropriately?

Table 3.7: *Future Research Directions*

other effects of interest (including instrumental and humanistic outcomes), such as AI delegation intentions, trust in AI, or the intention to follow AI advice. Thereby, we provide an answer to AI research that called for further exploration of metaknowledge in AI (Fügener et al., 2021a). Furthermore, the instrument can yield insights into the AI-specific aspects of technology acceptance. Potential applications are the assessment of AI literacy within different corporate functions and how it impacts the work, such as setting a strategic AI agenda for managers or how AI features are implemented by product managers. Third, the instrument constitutes a useful and universal tool for practitioners. Without focusing on a specific instance of AI or human role, it can be leveraged as a general tool in the organizational context. For example, it enables companies to analyze and define AI literacy requirements of different roles (product manager, top manager, developer, etc.). Consequently, the respective organizations can identify AI literacy deficits and set up targeted training programs for their employees. Lastly, our instrument's conceptualization structures future AI research within IS. Our five construct dimensions (adjusted model) invite several future research questions, which are discussed in the last subsection.

3.5 Limitations and Future Research

Our research has several limitations. First, while we deem the applied empirical tests for the first evaluation of the scale development appropriate, further steps (e.g., cross-validation) need to be applied to gain more validity (MacKenzie et al., 2011). Furthermore, our pre-test study was an online sample that pre-selects English-speaking subjects with access to a computer and, hence, a minimum level of general computer literacy, which likely impacts AI literacy. To gain additional insights, the sample needs to be extended to also include other segments of society. Lastly, our sample size was at the lower end of the recommended size, which invites future research to test the model with a larger number of observations.

Each of the identified construct dimensions poses an interesting future research direction. Further investigations within each dimension will not only enable further refinement of the instrument but also potentially uncover yet undescribed effects of AI. Potential research questions are summarized below (Table 3.7). The first question in each row exemplifies further AI content exploration, while the second question indicates potential paths to enhance the scale.

3.6 Appendix of Chapter 3

3.6.1 Appendix 3.A: AI Literacy Scale Items

Dimension		**ID**	**Item**
			All shown items are included in the *initial model* Δ-marked items are included in the *adjusted model*
			I have knowledge of...
AI technology knowledge		TK1	...of the types of technology that AI is built on?$^{\Delta}$
		TK2	...of how AI technology and non-AI technology are distinct?$^{\Delta}$
		TK3	...of use cases for AI technology?$^{\Delta}$
		TK4	...of the roles that AI technology can have in human-AI interaction
Human actors in AI knowledge		HK1	...of which human actors beyond programmers are involved to enable human-AI collaboration?$^{\Delta}$
		HK2	...of the aspects human actors handle worse than AI?$^{\Delta}$
		HK3	...of the aspects human actors handle better than AI?$^{\Delta}$
		HK4	...of the human actors involved to set up and manage human-AI collaborations
		HK5	...of the tasks that human actors can assume in human-AI collaboration
AI steps knowledge	Input	SK1	...of the input data requirements for AI?$^{\Delta}$
		SK2	...of how input data is perceived by AI
		SK3	...of potential impacts that input data has on AI
		SK4	...of which input data types AI can use
	Processing	SK5	...of AI processing methods and models?$^{\Delta}$
		SK6	...of how information is represented for AI processing
		SK7	...of the risks AI processing poses
		SK8	...of why AI processing can be described as a learning process
	Output	SK9	...of using AI output and interpreting it?$^{\Delta}$
		SK10	...of AI output limitations
		SK11	...of how to handle AI output
		SK12	...of which AI outputs are obtainable with current methods
			I have experience in...
AI usage experience		UE1	...in interaction with different types of AI, like chatbots, visual recognition agents, etc.?$^{\Delta}$
		UE2	...in the usage of AI through frequent interactions in my everyday life?$^{\Delta}$
AI design experience		DE1	...in designing AI models, for example, a neural network?$^{\Delta}$
		DE2	...in development of AI products?$^{\Delta}$
AI literacy (Overall items)		AIL1	In general, I know the unique facets of AI and humans and their potential roles in human-AI collaboration?$^{\Delta}$
		AIL2	I am knowledgeable about the steps involved in AI decision-making?$^{\Delta}$

Continued on next page

Continued from previous page

Dimension	**ID**	**Item**
	AIL3	Considering all my experience, I am relatively proficient in the field of AI?$^{\triangle}$

Table 3.8: *AI Literacy Scale Items*

3.6.2 Appendix 3.B: Literature Review Sources

#	**Search terms**	**Included journals & conferences**
1	**AI,** Artificial intelligence,	*Senior Scholars' Basket of IS Journals:* EJIS, ISJ, ISR, JAIS, JIT, JMIS, JSIS, MISQ
2	**IS / IT competenc*,** IS / IT capabilit*,	
3	**AI literacy,** AI competenc*, AI capabilit*	*1. Senior Scholars' Basket of IS Journals:* see above *2. AIS Special Interest Group AI:* DSS, ES, ES with Applications, IEEE IS, ISA *3. Key IS conferences:* AMCIS, ECIS, HICSS, ICIS

Table 3.9: *Literature Review Sources*

4 Enablement Development and Effects on Human Cognition

Title:	AiLingo – A Design Science Approach to Advancing Non-Expert Adults' AI Literacy
Authors:	Marc Pinski, Technische Universität Darmstadt, Germany Miguel-José Haas, Technische Universität Darmstadt, Germany Anjuli Franz, Technische Universität Darmstadt, Germany
Published in:	Proceedings of the Forty-Fourth International Conference on Information Systems. December 10-13, Hyderabad, India.
Available at:	www.aisel.aisnet.org/icis2023/learnandiscurricula/learnandiscurricula/10/

Abstract

Non-experts struggle in human-AI collaboration due to AI's differences from more traditional technologies, such as inscrutability. Meanwhile, information systems research on AI education primarily focuses on students in formal learning settings and neglects non-expert adults. Applying a design science research approach, we develop a learning application ("AiLingo") as an informal learning experience to advance non-expert adults' AI literacy. Based on self-determination theory, we deduct design principles and features tailored to non-expert adults. Through experimental evaluation (n = 101), we find that a learning experience with our design features present (vs. absent) leads to greater AI literacy advancement. Additionally, we find downstream effects of AI literacy, as it increases AI usage continuance intention and leads to a more positive attitude toward AI. Our study contributes to AI literacy and educational literature with a perspective on non-expert adults, novel design knowledge for AI education, and the discovery of crucial AI literacy consequences.

Keywords: AI Literacy, Informal Learning, Design Science Research

4.1 Introduction

Artificial intelligence (AI) has moved from the enclosed research labs of computer scientists into many parts of human life. For example, in the workplace, AI can act as an intelligent sales partner for marketing staff (Benbya et al., 2021) or as a reflection partner on diagnosis decisions for medical staff (Jussupow et al., 2021). Thus, other than the scientific and practitioner experts exploring AI's technical dimensions, "non-experts," such as employees from the business or medical domain, are now confronted with AI (Laupichler, Aster, & Raupach, 2023). As AI's capacities steadily increase (Berente et al., 2021), research and practice agree that the future of work and society will be based on the intense collaboration of humans and AI (Jain et al., 2021).

However, a workplace or society of mostly non-experts increasingly dependent on human-AI collaboration poses a substantial challenge. Especially non-experts struggle to interact with AI due to the three distinct facets that recent information systems (IS) research identified to distinguish AI from more traditional technology: increased autonomy, learning ability, and inscrutability to specific audiences or even everyone (Berente et al., 2021; Maitz et al., 2022; W. Yang, 2022). A survey of 3,000 managers identified a lack of AI skills as the primary barrier in the workplace when implementing AI (Brock & von Wangenheim, 2019). Such skill gaps can materialize when humans lose their trust in AI entirely after seeing it make only one mistake, not considering its ability to learn (Berger et al., 2020). They also manifest when non-experts mindlessly use recommendations from an AI-based HR tool, not considering the consequences of the tool's inscrutability or potential biases in the data it learns from (Newman et al., 2020). Such human behaviors exemplify how non-experts still primarily rely on mental models, like functional consistency, formed by education about and interaction with more traditional technology. In contrast, functionally inconsistent AI (i.e., with the ability to learn) might improve over time and necessitate erring to reach its desired target state (Schuetz & Venkatesh, 2020). Together, AI's distinct facets make it difficult to achieve efficient human-AI collaboration, especially for non-experts.

While IS researchers have identified this pressing issue, they have also begun investigating potential solutions. *AI literacy* refers to a human's AI skill set and describes the ability to use and critically evaluate AI as well as communicate and collaborate effectively with AI (Long & Magerko, 2020). Prior research suggests that AI literacy might be a powerful enabler in promoting purposeful human-AI collaboration (Long & Magerko, 2020; World Economic Forum, 2022b). As such an enabler, the literature asserts that AI literacy is a highly stakeholder-specific construct. For example, software developers, managers, and non-technical employees need different skills for their specific roles (Meske et al., 2020). However, when investigating how to advance AI literacy, there is a strong focus on university and K-12 students – or, in general: formal AI learning settings (Druga & Ko, 2021; Steinbauer et al., 2021).

In contrast, advancing AI literacy for *non-expert adults* and its consequences has been neglected, even though research is calling for more exploration in the field (Maitz et al., 2022). Given that human-AI collaborations will become more important in work and society, this paucity amplifies the current challenges of AI (Jain et al., 2021). Adults might not participate in formal AI learning settings as much as children and students who are naturally confronted with educational institutions integrating AI into their curricula (e.g., schools, universities, apprenticeships). However, due to the rapid impact of AI on job profiles, for example, of medical staff or HR managers, advancing AI literacy is also relevant for those who have finished their formal education or did not receive any training on the topic in their respective non-technical domain. In addition, adults' learning requirements in IS topics might differ significantly from those of students (Ghasemaghaei et al., 2019).

Yet, *informal AI learning settings* are currently an underexplored field of AI literacy research (Long, Blunt, & Magerko, 2021), and the literature calls for design innovations (Kim & Kwon, 2023). Informal learning settings are situated outside of formal educational institutions, for example, in a museum or while playing a game (Long, Blunt, & Magerko, 2021). The relevance of informal learning settings is underscored by literature suggesting that significant parts of science and technology learning happen outside of formal environments (Falk et al., 2016). Moreover, learning experiences in informal settings often reach a broader audience than formal courses, which often have higher (perceived) entry barriers (Long, Blunt, & Magerko, 2021). However, there are no mature insights on informal AI learning experiences for non-expert adults.

This study investigates the design and consequences of an informal AI learning experience tailored to non-expert adults. It is focused on supporting this neglected stakeholder group in their IS education by advancing their AI literacy, which is necessary to adapt to an AI-induced future. To investigate the consequences of advancing AI literacy, we shed light on two downstream effects that promote efficient human-AI collaboration: *AI usage continuance intention* and *attitude toward AI*. Human intentions and attitudes are critical outcomes in IS research (Bassellier et al., 2015). A sufficient intention to use AI and a positive attitude toward it are conditions for successful human-AI collaboration (Chiu et al., 2021). When the interacting humans are unwilling to work with an AI, the human-AI collaboration has little chance of achieving its purpose. Similarly, researchers call to address non-experts' potentially negative attitudes toward AI to prevent societal harm and inform potential social applications of AI (Selwyn & Gallo Cordoba, 2021). Thus, this study formulates two research questions:

> *RQ1: How can the AI literacy of non-expert adults be advanced in an informal learning setting?*
>
> *RQ2: How does an advancement of non-expert adults' AI literacy affect their AI usage continuance intention and their attitude toward AI?*

We followed a design science research (DSR) approach to address these research questions and adhered to DSR principles and guidelines in IS (Hevner et al., 2004; Peffers et al., 2014). After establishing problem awareness, we deducted theory-driven design requirements (DR) and corresponding design principles (DP) using self-determination theory (SDT) as our kernel theory (Deci & Ryan, 1985). We instantiated the derived DPs in design features (DF) of the central design artifact of the study – an AI learning application for non-expert adults ("AiLingo"). We evaluated our application with an online experiment (n = 101), where non-experts downloaded and used AiLingo on their phones, measuring the advancement of the participants' AI literacy and downstream effects on AI usage continuance intention and attitude toward AI.

The contributions of our paper are threefold: (1) While previous research focused on advancing AI literacy for students in formal learning settings (Druga & Ko, 2021), we present a complementary perspective focused on informal learning settings tailored to non-expert adults. Our findings contribute to IS education research by providing prescriptive design knowledge through theory-driven and empirically evaluated DPs for informal AI literacy learning experiences, facilitating greater learning success than a learning experience not employing these DPs. (2) We depart from prior research on the consequences of AI literacy, which finds it enhancing human abilities, like delegation and critical assessment ability (Pinski, Adam, & Benlian, 2023; Schoeffer et al., 2022), and provide a view on human intentions and attitudes. Through evaluating our design artifact, we contribute to understanding AI literacy's consequences for non-expert adults by demonstrating that advancing one's AI literacy leads to higher AI usage continuance intention and a more positive attitude toward AI. (3) Regarding practice, our findings carve out implications for the design of AI literacy upskilling programs by providing design knowledge in the form of concrete and evaluated DFs.

The developed DFs can help practitioners improve AI literacy programs regarding effectiveness, comprehensiveness, and reproducibility. Thus, we extend the range of options on how to teach in IS.

The paper is structured as follows: After revisiting the theoretical background, the methodology section provides information on the employed design science phases. Then, we elaborate on the design process of AiLingo, followed by its evaluation process, including the research model, hypotheses, experimental design, and results. Last, we discuss the paper's contributions and point out limitations and future research.

4.2 Conceptual Background

4.2.1 Difficulties in Human-AI Collaboration

AI has long passed the threshold where it can only be considered from a technological viewpoint. It has permeated many parts of human life, such as health, mobility, and finance (Berente et al., 2021). Non-experts are confronted with AI in their daily lives and must interact with it, for example, when scrolling through a social media feed or using an internet search provider. Similarly, businesses will integrate AI into many work processes of non-expert employees due to the significant value its increased capacities are projected to generate compared to more traditional technology (Collins et al., 2021). While AI is highly potent in some tasks, studies have shown that humans and AI possess complementary competencies. For instance, AI's ability to recognize patterns makes it accurate in image classification, but some images necessitate interpretation of the social context in which humans excel (Fügener et al., 2021a). Therefore, IS researchers and practitioners largely agree that AI will not simply replace humans for many tasks but that the collaboration of humans and AI will become a common configuration in the workplace, even for humans without prior technical education (Jain et al., 2021).

With human-AI collaboration believed to be of great importance in our future workplaces and society, it becomes alarming that researchers found particularly non-experts, who comprise the majority in the workplace, struggling to collaborate with AI (Dietvorst et al., 2018; Schmidt et al., 2020). AI's distinct facets compared to traditional technology, namely its increased autonomy, learning ability, and inscrutability, break assumptions that interaction with technology has been built on for decades (Berente et al., 2021; Schuetz & Venkatesh, 2020). For instance, when using technology without the ability to learn, it might be beneficial to stop using it as soon as it errs because errors will be repeated, given that the system is functionally consistent. In contrast, AI can learn and improve over time, sometimes necessitating to err to reach its target state through feedback. Mental models for technology interaction built on assumptions, like functional consistency or transparency, are leading to significant AI interaction problems. For example, studies show that humans tend to have less trust in AI by default (Schmidt et al., 2020) and lose their trust entirely after seeing an AI err only once (Dietvorst et al., 2018). These problems in human-AI collaboration are amplified for non-experts, who often have a particularly vague understanding of what AI refers to and how it works (Maitz et al., 2022). For instance, Maitz et al. (2022) found in an interview study that many construction workers associate AI with "something with computers or with robots" (p. 391). Taken together, non-experts cannot be expected to collaborate with AI efficiently without a basic understanding of AI functioning.

4.2.2 AI Literacy as an Enabler of Human-AI Collaboration

The concept of technology literacy is not new in IS research (Bassellier et al., 2003). For instance, IS scholars have conceptualized computer literacy to guide the education of IS professionals or students (Bassellier et al., 2015). Technology-related literacy gained broader relevance with the increasing technologization of the workplace and society. Researchers defined different literacies, for example, digital literacy (Gilster, 1997) and data literacy (Someh et al., 2019). However, AI literacy distinguishes itself from these prior literacy concepts because AI breaks assumptions held in IS for decades (as explored above), necessitating new skill sets to enable human-AI collaboration (Berente et al., 2021).

While much research focused on optimizing AI features from a technological perspective to enable necessary human-AI collaboration, only recently, the complementary stream of AI literacy research formed, approaching the problem from a human-centered perspective (Heyder & Posegga, 2021; Long & Magerko, 2020; Ng et al., 2021). AI literacy refers to a *set of human competencies that enables humans to evaluate AI, communicate and collaborate with AI, and use AI as a tool* (Long & Magerko, 2020). When exploring and describing AI literacy, the literature has ascribed a broad set of competencies to the emergent concept. Research agrees that AI literacy consists not only of technical skills (e.g., AI development) but also a wide range of skills relating to the social context, such as the ethical judgment of an AI in a specific use case (Heyder & Posegga, 2021; Pinski & Benlian, 2023). Furthermore, IS research emphasizes that AI literacy is a stakeholder-specific concept, meaning different stakeholders (e.g., developers, managers, and non-technical employees) necessitate individualized skill sets (Benlian, 2022; Meske et al., 2020). However, studies so far primarily focus on students often situated in formal learning settings (Steinbauer et al., 2021).

While non-experts have largely been neglected by AI literacy research, many studies within the literature point toward the potential beneficial effects of AI literacy, which would also greatly benefit non-experts in their personal and work lives. For example, AI literacy has been shown to improve performance in delegation-based human-AI collaboration (Pinski, Adam, & Benlian, 2023). Also, AI literacy has been significantly associated with perceived informational fairness (Schoeffer et al., 2022). On the other hand, AI literacy can also contribute to the ability to critically assess AI (Druga & Ko, 2021). In summary, despite the increasing number of studies on AI literacy, informal AI literacy education for non-experts is an underexplored but highly relevant field of research.

4.2.3 Self-Determination Theory

When following a DSR approach, it is vital to employ a kernel theory that advises the design process from a theoretical ground (Kuechler & Vaishnavi, 2012). We draw on SDT, an established theoretical framework that IS research frequently employed, for example, in cybersecurity education studies (Silic & Lowry, 2020). We leverage SDT to deduct the DPs that guide the development process of our AI learning experience. In general, SDT aims to explain intrinsic human motivation, making it a suitable framework to explain the factors that drive a human's motivation to learn (Deci & Ryan, 1985). SDT also emphasizes that a non-supportive setting can easily disrupt intrinsic motivation, underlining the need for a supportive learning experience tailored to non-experts. Furthermore, many IS gamification studies leverage SDT, given that gamification's educational goal is to facilitate greater motivation and engagement for a topic (D. Liu et al., 2017; Oppong-Tawiah et al., 2020).

SDT states three factors that induce a feeling of self-determination in humans and contribute to the intrinsic motivation for an activity, such as learning a new topic: (1) competence, (2) autonomy, and (3) relatedness (Deci & Ryan, 1985). (1) To adopt an external objective as one's own, one has to feel effective. If learners comprehend a goal and possess the necessary abilities to achieve it, they are more likely to accept and internalize it. According to SDT, experiencing *competence* facilitates the internalization of a learning goal (Ryan & Deci, 2000). A feeling of competence can be induced, for example, through the right tasks and feedback. (2) One who is excessively controlled not only loses initiative but also does not do well when learning, particularly when the learning is complex or calls for creative processing. Similarly, research indicates that children of more *autonomy*-supportive parents are more mastery-oriented and more prone to impulsively explore and challenge themselves than children of more controlling parents (Ryan & Deci, 2000). (3) A sense of belongingness provides the groundwork for intrinsic motivation (Ryan & Deci, 2000). When one experiences *relatedness* to a group in the learning context, one is more likely to engage in the learning activity. Accordingly, one is also more likely to engage in actions that others regard favorably, whether that be a family, a peer group, or a society to whom one feels (or would like to feel) connected. For instance, relatedness to teachers was associated with greater internalization of school-related behavioral regulations (Ryan & Deci, 2000).

4.3 Methodology

We applied a DSR approach to develop, test, and refine an informal learning experience, aiming to advance individuals' AI literacy, ultimately increasing their AI usage continuance intention and attitude toward AI. DSR has become a well-accepted approach within IS research in recent years (Hevner et al., 2004; Kuechler & Vaishnavi, 2012; Peffers et al., 2014). With DSR, researchers create and evaluate new and useful artifacts to solve real-world problems relevant to practice, impacting individual, organizational, or societal stakeholders (Kuechler & Vaishnavi, 2012). For example, IS research used DSR to develop a mobile app encouraging sustainable workplace behaviors (Oppong-Tawiah et al., 2020) or to create IS-promoting habit formation (Chung et al., 2021).

We followed the five-step design research cycle (I-V) introduced by Kuechler and Vaishnavi (2012), broadly adopted by previous DSR literature (Peffers et al., 2014). The design cycle provides a structured process for conducting rigorous design research. This paper elaborates on the first design cycle while highlighting upcoming cycles in the future research section. Each iterative process step contains specific DSR activities that result in a DSR outcome (see Figure 4.1): First, we established **(I) problem awareness** (i.e., lack of informal AI learning experiences for non-experts, see introduction and theoretical background section). During **(II) suggestion**, we deducted theory-driven DPs using SDT. Then, we instantiated the DPs into DFs of the AI learning application in the **(III) development** step. For **(IV) evaluation** regarding learning success, AI usage continuance intention, and attitude toward AI, we conducted an online experiment. Specifically, we compared one group learning with the AiLingo learning application (where the SDT-based DFs are present) with another group learning with a simple text-based learning application (where the SDT-based DFs are absent). Finally, we draw **(V) conclusions** for theory and practice.

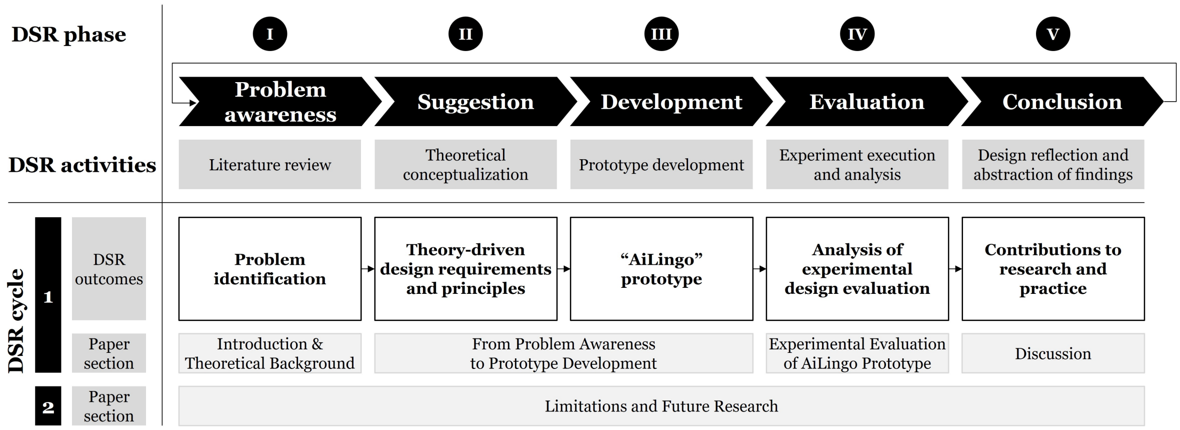

Figure 4.1: *DSR Approach (adapted from Kuechler and Vaishnavi, 2012)*

4.4 From Problem Awareness to Prototype Development (DSR Phase II-III)

4.4.1 Theory-driven Deduction of Design Principles (DSR Phase II)

After establishing awareness regarding the lack of informal AI education for non-experts, we deduct DRs and DPs to guide the development of DFs for a potential design solution. We use a theory-driven approach to deduct the DRs and follow prior IS research, employing such an approach, for example, to design conversational dashboards (Ruoff et al., 2021) or recommender systems (Arazy et al., 2010). Based on the three components of SDT, we deduct three DRs contextualized to the non-expert AI learning context. These contextualized DRs result in three DPs for informal learning experiences tailored to non-experts. In the following, we describe the deduction of each DP (see Figure 4.2).

Intuitive AI function understanding (DP1). According to SDT, the experience of competence is essential for promoting intrinsic motivation to learn and understand a specific topic (Deci & Ryan, 1985). Specifically, for a complex subject such as AI, ensuring that the learner experiences sufficient mastery is vital. Furthermore, there are many misconceptions among non-experts about what AI is and how it functions (Maitz et al., 2022; Selwyn & Gallo Cordoba, 2021). Thus, we formulate a first requirement for designing an informal learning experience for non-experts (DR1): *"Let learners experience competence and learning progress by addressing common AI misconceptions of non-experts."* Based on DR1, we deduct DP1: *"Provide a learning experience that conveys intuitively how AI functions, compared to more traditional computing techniques."* The principle emphasizes that the learning experience should present AI functioning as intuitively as possible. Particularly, the learning experience should not require any prior knowledge, which would set up entry barriers for non-experts. Meanwhile, the learning content should fall outside the learners' comfort zone while still being perceived as attainable. In addition, DP1 emphasizes that the intuitive content should transport the specificities of AI to achieve the learning objectives of resolving AI misconceptions and establishing AI competence. Potential means of intuitive understanding are analogies, simplifications, or visuals (He et al., 2022).

Interactive, non-expert-friendly elements (DP2). The ability to make autonomous choices contributes to intrinsic learning motivation (Deci & Ryan, 1985). On the other hand, choices can also be confusing or overwhelming for humans if they do not match their competence level (Q. Wang & Shukla, 2013). Hence, we establish DR2: *"Offer learners interactive elements and choices tailored to non-experts."* Given DR2 and DR1, we specify DP2, *"Provide a learning experience that has AI-specific, interactive elements with non-expert-friendly options."* A potential AI interaction that leaves room for autonomy and supports an AI function understanding is AI development. A learning experience could leverage humans' autonomy within such a process on a high level to fulfill two goals. First, an open-ended, iterative configuration of an AI gives the learner autonomy in the configuration process of development. However, the designer should ensure that the configuration options are appropriate for non-experts to avoid inducing a feeling of incompetence. Second, an iterative configuration enables the designer to convey a feeling of competence (DR1) when the learner comprehends with each iteration more about how an AI functions, for example, because the model accuracy improves through exploration by the learner. In summary, DP2 supports DR2 and DR1.

Real-life relatable AI examples (DP3). Relatedness to others is the third factor contributing to the intrinsic motivation of humans (Deci & Ryan, 1985). To address the human need for relatedness in the AI learning experience, we formulate DR3: *"Showcase AI applications that are relatable for non-experts."* Presenting humans with AI applications that affect groups of non-experts relatable to them should increase their intrinsic motivation to understand AI. Since it is important that the learner feels connected to the affected group in the presented AI example, the examples should be real with an easily identifiable group. Once one moves from abstract AI functioning to real-life examples and consequences for peers, they can understand themselves as part of a group that needs to understand AI better, for example, to empower oneself to prevent adverse impacts of AI. Therefore, we deduct DP3 from DR3: *"Provide a learning experience that uses real-life AI examples conveying AI-specific advantages and disadvantages for use cases relevant to non-experts."* Furthermore, different use cases can be a potential tool to exemplify abstract AI advantages and disadvantages, like "black box nature," in real-life settings that are relatable for non-experts.

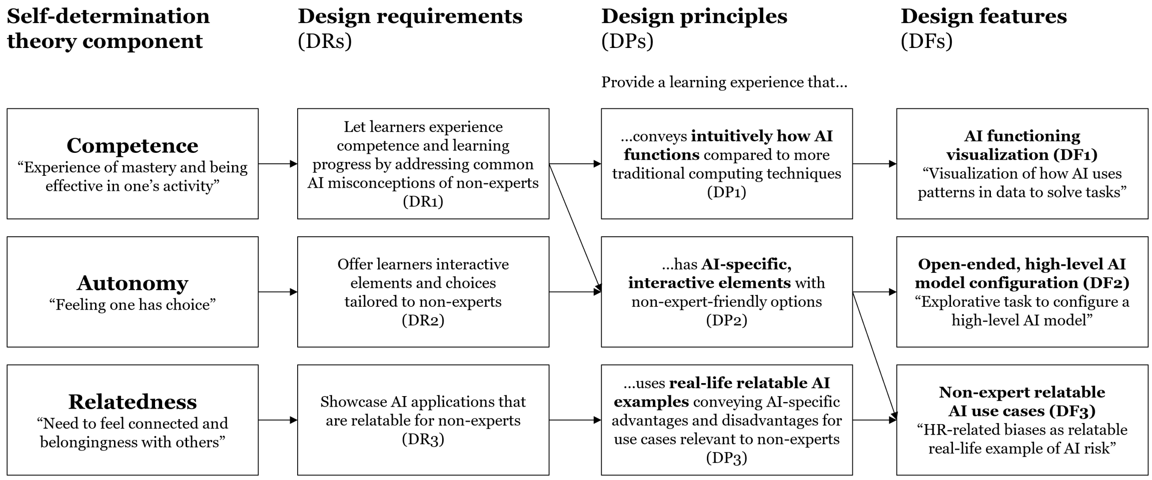

Figure 4.2: *Design Requirements, Principles, and Features Informed by SDT*

4.4.2 Design Feature Instantiation (DSR Phase III)

After the DP deduction, we instantiated each abstract DP as a specific DF of AiLingo, aiming to develop a learning app that adults can use easily. We developed and distributed (Android and iOS) AiLingo using Expo, an open-source framework that builds on React Native, enabling cross-platform development and distribution of mobile apps with a single JavaScript code base. We proceed with a description of the DFs:

AI functioning visualization (DF1). We instantiated DP1 (*"Provide a learning experience that conveys intuitively how AI functions compared to more traditional computing techniques."*) through visualization as DF1. AiLingo explains that an AI (in this case, a neural network for image classification) does not "think" like a human but exploits data patterns to make its prediction. The learner uses an AI model simulator that simulates the training of a model that distinguishes images of dogs and muffins with similar color patterns (three dark circles on a light background, see Figure 4.3, DF1). In the AI model simulation, the learner labels the image classes an image classification model would use for training, like Google's Inception V3. While humans typically can distinguish the image classes, DF1 shows the learner conceptually that if an AI model is provided with insufficient training data (i.e., in the simulation, up to 6 images to make the training game not time-consuming), it cannot distinguish the image classes due to their visual pattern similarity. Thus, DF1 intuitively conveys how neural networks learn based on data patterns.

Open-ended, high-level AI model configuration (DF2). The images learners are presented with as part of DF1 belong to an AI model configuration task. In the AI model configuration task, the learner assigns different training images to image classes and subsequently "trains" the AI model based on the input. The task is set up iteratively and lets the learners autonomously choose how long they want to keep optimizing the model. AiLingo instantiates DP2 (*"Provide a learning experience that has AI-specific, interactive elements with non-expert-friendly options."*) by letting the learner configure an image classification AI without requiring the user to have technical skills. Technically more complex aspects of the model configuration are executed in the background, reducing the learner's configuration options to the essential decisions of which and how many images one wants to use for the training process. Hence, DF2 gives the learner non-expert-friendly autonomy in the learning process.

Non-expert relatable AI use cases (DF3). The instantiation of DF3 was guided by DP2 and DP3. Therefore, AiLingo first informs the learners about real-life cases of AI failure in domains relatable to non-experts. For instance, based on DP3, the learner receives central information about a hiring AI at Amazon that reproduced sexist biases (Dastin, 2018). Then, based on DP2, the learner receives multiple-choice questions as interactive elements probing whether one understood why and how the mistake happened through the AI (Figure 4.3, DF3). Thus, DF3 aims to present learners with situations they can imagine themselves in and feel connected with the affected group (i.e., being a job applicant that an AI assesses). Similarly, it seeks to explain in a playful way why the (dis)advantages of the respective AI played out the way they did to increase the learner's understanding of the applicability of AI, AI risk, and AI functioning.

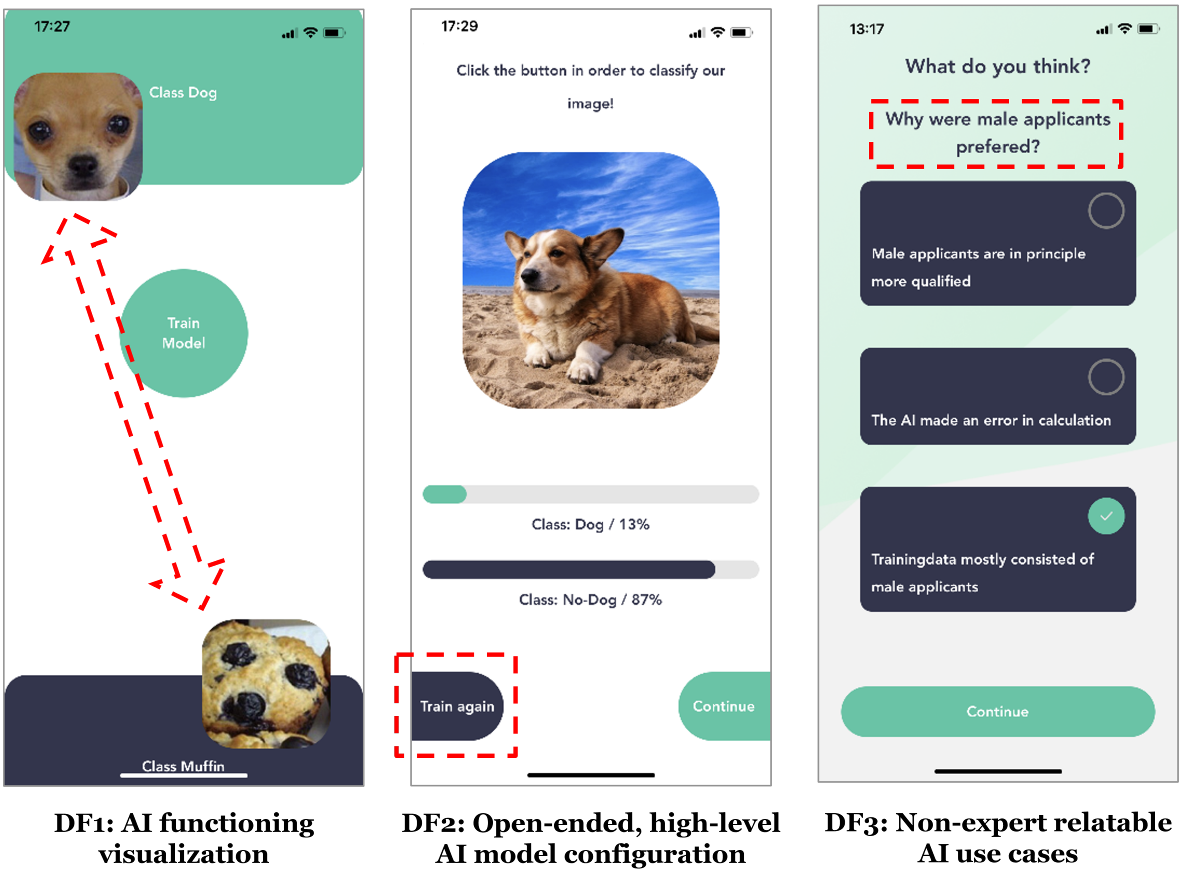

Figure 4.3: *Design Features from AiLingo Prototype*

4.5 Experimental Evaluation of AiLingo Prototype (DSR Phase IV)

4.5.1 Research Model and Hypotheses for Experimental Prototype Evaluation

To demonstrate and evaluate the suggested AiLingo prototype and answer our research questions, we developed a research model including our evaluation criteria. Following prior DSR studies in IS, we evaluated all developed DPs cumulatively in this first design cycle (Toreini et al., 2022). We used a difference-in-difference research design to compare the change in (Δ) participants' AI skills, intentions, and attitudes from before (t1) to after the learning experience (t2) between two groups (AiLingo group vs. control group). As such, the independent variable (design configuration of the learning experience) is binary: In the AiLingo group, the SDT-based DFs are present (=1), whereas in the control group, they are absent (=0), leading to a regular text-based learning experience with the same learning content, however omitting the DFs such a visualization. We evaluated "Δ AI Literacy" as the primary evaluation criteria and "Δ AI Usage Continuance Intention" and "Δ Attitude Toward AI" as further downstream effects. In the following, we elaborate on each hypothesized relationship in Figure 6.2.

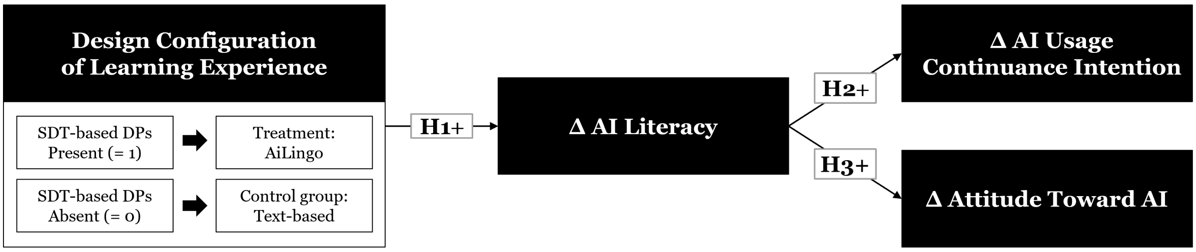

Figure 4.4: *Research Model for Experimental Prototype Evaluation*

SDT states that competence, autonomy, and relatedness are the three key factors that foster intrinsic motivation (Deci & Ryan, 1985). AiLingo is a learning experience based on DFs deducted from DPs following SDT, as outlined above. Prior research has shown that a greater intrinsic learning motivation is commonly associated with greater learning success, for example, leading to better information retention (Ninaus et al., 2017). We also expect a text-based learning experience to enhance learners' AI literacy because they receive the same content. However, due to the lower expected intrinsic motivation compared to the AiLingo learning experience, we expect less learning success compared to the AiLingo learning experience. To test if AiLingo enhances "regular" text-based learning and to account for the baseline AI literacy of the respective learner, we evaluate the change in (Δ) AI literacy between t1 and t2. Thus, we formulate the following hypothesis for the primary evaluation of AiLingo:

> H1: A learning experience where SDT-based DFs are present leads to a greater positive change in AI literacy than a learning experience where SDT-based DFs are absent.

AI usage continuance intention is a crucial metric for human-AI collaboration (W. Yang, 2022). Whereas prior IS research established continuance intentions (Bhattacherjee, 2001), we lack insights into advancing its AI-specific counterpart. Thus, we investigate this potential downstream effect as an additional evaluation criterion. Prior research has identified several positive effects of AI literacy on human-AI collaboration. For instance, more AI-literate humans tend to do better at AI delegation (Pinski, Adam, & Benlian, 2023). Following SDT, an increased feeling of competence, for example, due to better AI delegation, should increase the intrinsic motivation to continue using AI (Deci & Ryan, 1985). Furthermore, AI literacy positively affects perceived fairness (Schoeffer et al., 2022). Higher perceived fairness in AI also conceivably increases AI usage continuance intention. Thus, based on the positive effects that prior AI literacy literature identified, we formulate the following hypothesis:

> H2: A high (vs. low) change in AI literacy leads to a positive change in AI usage continuance intention.

Next to AI usage continuance intention, one's attitude toward AI is also a crucial metric for productive human-AI collaboration (Long, Blunt, & Magerko, 2021). AI's impact on the work environment has a significant potential to induce a negative attitude toward AI, for example, when humans fear for their employment or known work routines (Maitz et al., 2022; Selwyn & Gallo Cordoba, 2021). If humans possess a negative default attitude toward AI, it is much less likely that a human-AI collaboration will achieve its intended outcomes. Prior research has shown that educational programs can reduce computer anxiety (Nomura et al., 2006). Furthermore, prior AI literacy research has also shown that AI literacy can increase AI delegation ability, resulting in better human-AI team performance (Pinski, Adam, & Benlian, 2023). Increased team performance allows the interacting human to experience AI's upsides while underscoring the importance of the human role, thus likely causing a more positive attitude. Hence, we formulate the following:

> H3: A high (vs. low) change in AI literacy leads to a positive change in attitude toward AI.

4.5.2 Experimental Design

4.5.2.1 Procedure and Participants

Experimental evaluation is common practice in DSR studies (Toreini et al., 2022). We used an online experiment to evaluate our AiLingo prototype and test the corresponding research model. The experiment consisted of a treatment group using AiLingo (i.e., with present SDT-based DFs) and a control group, where SDT-based DFs are absent (=0), leading to a regular text-based learning experience with the same learning content. We recruited a representative sample of n = 101 participants from the provider Prolific, commonly used for software evaluation and online experiments (Palan & Schitter, 2018). We excluded participants with AI development experience and those younger than 18 years old to receive a non-expert adult sample (from 118 invited participants, 53 participants remained in the treatment group and 48 participants in the control group). At the beginning of the experiment, we asked the participants to download the AiLingo app (or the "control group app," depending on their group) onto their own mobile phones. As such, the participants are situated in a realistic informal learning setting. The whole learning experience took place within the app. Before starting the learning content, the participants answered demographic questions and baseline questions regarding their AI literacy, AI usage continuance intention, and attitude toward AI. Then, each participant engaged with the learning content. The control group received the content as one single text they scrolled through in the control group application, similar to a textbook section. In contrast, the AiLingo treatment group received the learning content through the SDT-based DFs described above. After finishing the learning experience, we recorded the study's principal variables again.

In our sample, the participants were 31.4 years old on average. 66% were male, 34% were female, and 0% identified with other genders. Regarding the level of education, 73% had a university degree, 17% had a high school diploma, 6% had an apprenticeship, and 4% had another or no degree. The sample was distributed across all fields of employment, with the largest five being "Information and communication activities" (17%), "Professional, scientific and technical activities" (15%), "Health and social work activities" (13%), "Financial and insurance activities" (12%), "Other business activities" (10%). Considering all participant statistics above, we deem the sample appropriate to assess non-expert adults' AI literacy advancement.

4.5.2.2 Measures and Validation

Prior research has shown that objective and subjective literacy are mildly correlated at best, with the correlation becoming weaker for complex topics, such as AI (Klerck & Sweeney, 2007). To evaluate our prototype's learning experience, we aimed to use an objective measurement of AI literacy to reduce the potential bias of the perception of one's literacy (e.g., overconfidence bias), as practiced in other non-AI studies regarding the advancement of knowledge (T. H. Nguyen et al., 2017). Due to the lack of an objective scale for AI literacy in the literature, we developed a set of multiple-choice questions to test the participant's AI literacy objectively, as practiced, for example, in psychological research (T. H. Nguyen et al., 2017). Following traditional construct development procedures in IS (MacKenzie et al., 2011), the questions are grounded in AI literacy literature (see Table 4.3) and based on discussions with experts from the field ($n = 11$). Among the interviewed experts were four senior scholars (IS and management professors), four junior researchers (IS and management post-docs and Ph.D. students), and three practitioners (professionals working with AI). The expert interviews were aimed at resolving ambiguity and ensuring validity of the questions and answers. Each of the twelve developed AI questions was presented to the participants with two answer options, of which none to both can be correct.

For the remaining two downstream variables, we leveraged established 7-point Likert scales (1 = "Strongly disagree" to 7 = "Strongly agree"). Specifically, we used the IS continuance scale from Bhattacherjee (2001) and the attitude toward robots scale from Norman and Skinner (2006). We made the scales AI-specific by replacing the representative term for "IS" and "robot" with the term AI (see Table 4.4). Table 4.1 provides descriptive statistics and correlations to validate the scales and the measurement model. AI usage continuance intention and attitude toward AI satisfy the commonly used thresholds for internal consistency, with Cronbach's alpha (CA) and the composite reliability (CR) exceeding .8 (MacKenzie et al., 2011). We find support for discriminant validity since the correlations among all variables were smaller than the square root of their average variance extracted, satisfying the Fornell-Larcker criterion (Fornell & Larcker, 1981). Variance inflation factors (VIF) were below 5, suggesting no multicollinearity issues.

4.5.3 Results

We used an ordinary least squares regression model with the statistical software "R" (version 4.2.0) to analyze our data. We set up one regression model for each hypothesis (see Table 4.2). In each model, we controlled for age and gender effects. In the following, the results are reported in the order of the presented hypotheses:

H1 stated that a learning experience where SDT-based DFs are present leads to a greater positive change in AI literacy than a learning experience where SDT-based DFs are absent. We tested H1 with model 1 in Table 4.2 and found that an SDT-based design configuration positively affects Δ AI literacy ($\beta = 1.831, p < .001$). Thus, we conclude **support for H1**.

Looking at the downstream effects, H2 stated that a high (vs. low) Δ AI literacy increases Δ AI usage continuance intention. We tested H2 with model 2 in Table 4.2 and found that Δ AI literacy positively affects Δ AI usage continuance intention ($\beta =$

$.062, p < .1$). Therefore, we find **support for H2**. The second downstream hypothesis (H3) stated that a high (vs. low) Δ AI literacy increases Δ attitude toward AI. We tested H3 with model 3 in Table 4.2 and found that Δ AI literacy also positively affects Δ attitude toward AI ($\beta = .080, p < .05$). Hence, we find **support for H3**.

Variable	**T^{C}**	**M**	**SD**	**CA**	**CR**	**VIF**	**Correlations** (Square root of AVE on diagonal axis) AIL	ACI	ATA
AI literacy^{A} (AIL)	t1	6.39	2.09	N/A	N/A	1.10	N/A		
	t2	7.95	2.52						
AI usage continuance intention^{B} (ACI)	t1	5.78	1.17	.93	.91	1.07	.42	**.83**	
	t2	5.89	1.07						
Attitude toward AI^{B} (ATA)	t1	3.84	1.13	.82	.81	1.10	(.31)	(.56)	**.58**
	t2	3.82	1.21						

A. Measured with multiple-choice questions; B. Measured with a 7-point Likert scale; C. Time: t1 = Before learning experience, t2 = After learning experience; D. N/A due to multiple-choice scale CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted, VIF = Variance Inflation Factor

Table 4.1: *Descriptive Statistics and Correlations*

Variable \ **DV**	**AI literacy (1)** β	s.e.	**AI usage continuance intention (2)** β	s.e.	**Attitude toward AI (3)** β	s.e.
Intercept	.157	.845	(.016)	.320	(.088)	.313
Manipulation						
Design configuration^{A}	1.831***	.432				
Δ AI literacy			.062+	.037	.080*	.036
Controls						
Age	.028	.021	.006	.009	.007	.008
Gender^{B}	(.632)	.459	(.241)	.184	(.346)+	.180
$\mathbf{R^2}$	.19		.06		.11	

A. SDT-based DFs present = 1, SDT-based DFs absent = 0; B. Male = 1, female = 0, no one chose the option "other." Significance levels: $+ = p < .1$, $* = p < .05$, $** = p < .01$, $*** = p < .001$

Table 4.2: *Regression Results*

4.5.4 Supplementary Evaluation

For user-focused design artifacts, DSR research mentions user experience as an important evaluation criterion (Ninaus et al., 2017). Next to the main evaluation of our design artifact above, we thus conducted a supplementary evaluation targeting not the learning success (i.e., Δ AI literacy) but rather the user experience during learning. At the end of the learning experience in both groups, we captured user engagement, interest, and intention to explore the topic further as three critical user experience metrics, using established scales (A. Chen et al., 1999; Wiebe et al., 2014). We conducted two-sided t-tests and found that for each metric, the AiLingo group scored significantly higher ($p < .001$) than the control group. Thus, we conclude that the AiLingo prototype leads to better learning outcomes, as explored above, and provides a more user-friendly learning experience. As non-expert adults might engage with AI voluntarily compared to students who are confronted with the topic in formal learning settings (e.g., school), these findings underline that the developed prototype is purposeful for non-expert adults who might necessitate a more engaging learning experience to continue their own AI education.

4.6 Discussion (DSR Phase V)

In this study, we followed a DSR approach to develop an AI learning app (AiLingo) as a usable design artifact to advance the AI literacy of non-expert adults in an informal learning setting. Additionally, we assessed the downstream effects of AI literacy on AI usage continuance intention and attitude toward AI. We find that a design configuration of an informal learning experience where SDT-based DFs are present (vs. absent) leads to a greater increase in AI literacy. Thus, we provide a strategy for educating non-expert adults regarding AI with a concrete example of a learning experience design and insights into how it influences critical human downstream outcomes. Specifically, we make two contributions to AI literacy and educational IS literature with this study:

First, we *provide valuable design knowledge in the form of theory-driven and empirically evaluated DPs for informal AI literacy learning experiences tailored to non-expert adults.* Prior research has focused on formal learning experiences for university or K-12 students, mostly conceptualizing curricula (Druga & Ko, 2021; Steinbauer et al., 2021). To the best of our knowledge, our DSR project is the first to investigate an SDT-based informal AI learning experience specifically tailored to non-expert adults. We extend AI education research on learning experience design with general DPs. These DPs are not specific to a particular learning experience, thus ensuring generalizability. They apply to diverse informal learning experiences, such as mobile apps, online learning, exhibitions in public places, or when educating users of AI during human-AI interactions through educational features of the AI itself. Furthermore, the DPs recognize AI-specificities, such as common misconceptions of non-experts about what constitutes AI (Maitz et al., 2022). Through our experimental design evaluation, we find support that the deduced general DPs lead to a greater learning success of non-experts compared to a control group. Additionally, we provide further evidence with our supplementary evaluation that AiLingo enhances the overall user experience, which promotes voluntary learning.

Second, we *extend our understanding of the consequences of AI literacy* by uncovering that increased AI literacy leads to higher AI usage continuance intention and a more positive attitude toward AI. While prior research on the consequences of AI literacy is scarce, the few existing studies on the topic primarily identified AI literacy's enhancing effect on specific abilities in relation to AI, such as AI delegation ability (Pinski, Adam, & Benlian, 2023) or critical assessment ability of AI (Druga & Ko, 2021). In contrast, we know little about how to promote human intentions and attitudes concerning AI. However, these insights are needed because both can significantly impact the success of human-AI collaborations (P. Zhang, 2013), and humans are prone to develop negative attitudes toward AI specifically since there are many misconceptions among non-experts (Maitz et al., 2022). By evaluating our design artifact (AiLingo), we extend the literature on AI literacy's consequences, with a perspective on intentions and attitudes complementing prior ability-focused research on its consequences.

Our findings also *provide concrete design recommendations relevant to different practitioner types*. So far, designers have not provided convenient informal learning experiences for non-expert adults. Next to the general DPs, this study provides an actionable solution for instantiating the deducted principles in the form of specific DFs. These DFs can either be directly leveraged by designers of AI literacy upskilling programs or can act as a starting point for developing more refined DFs in other informal learning experiences, such as exhibitions in public places. Our design evaluation supports the positive effects of the DFs on learning success, thus helping practitioners to improve informal AI literacy learning experiences regarding effectiveness, comprehensiveness, and reproducibility. Advancing AI literacy will be important for companies to ensure that the workplace of the future is efficient and ethical, taking into account the needs of their non-expert employees, but also for governments and societies to prevent societal harm to communities or minorities (Spiekermann et al., 2022). For instance, government organizations could use this study's design knowledge on informal learning experiences to adhere to their educational mandate for their citizens by creating informal public AI education. Thus, the design knowledge on advancing non-expert AI literacy provided by this study is highly relevant to diverse practitioner stakeholders.

4.7 Limitations and Future Research

DSR is an iterative approach aiming to improve the design artifact with each iteration (Hevner et al., 2004). This study represents the first DSR cycle resulting in the AiLingo prototype, as presented in the paper. However, our suggestion, development, and evaluation have certain limitations, which pose promising directions for future research as well as future DSR cycles of the AiLingo project.

First, we did only assess short-term learning effects in our current evaluation. The participants using AiLingo assessed their level of AI literacy directly after finishing the learning experiences. It would be of great interest to test how persistent the learning effects are over time. Future research or a second design cycle could aim for a long-term evaluation of the learning experience, testing the retention of AI literacy after a week or a month. Furthermore, future studies or design cycles could extend AiLingo with different learning nuggets intended to be completed over several days. Existing (non-technology) informal learning experiences based on mobile apps like “Babbel” for learning languages aim to develop learning routines. Hence, AiLingo or similar informal learning experiences could aim to keep the learner engaged and test the effect on AI literacy learning success and other downstream outcomes of interest.

Second, AiLingo was developed to promote a general understanding of AI for non-experts. The evaluation design did not allow for testing if non-experts were able to apply their gained general AI understanding to their specific personal context. Future research or design cycles could seek out a business or societal context where non-experts are confronted with a specific introduction of an AI application in their current environment, for example, a company introducing a recommendation AI for sales agents. Then, one could test if general AI understanding is sufficient for non-experts to promote efficient human-AI collaboration or if they necessitate a context-specific learning experience.

Finally, in this first design cycle, our evaluation assessed the cumulative effect of DF1, DF2, and DF3, in line with other DSR studies entering a new field (Toreini et al., 2022). However, the distinct effects of each DF would be of great interest in future design cycles to optimize each feature further. Future studies could aim for a broader evaluation with multiple test groups to assess the features’ individual and combined effects on learning success and user experience.

4.8 Conclusion

Employing a DSR approach, this study developed a mobile application as an IT artifact that facilitates an informal learning experience to advance the AI literacy of non-expert adults. We found that an SDT-based design configuration of the learning experience positively affects the advancement of non-experts' AI literacy. Additionally, we assessed the downstream effects of increased AI literacy and found it increased AI usage continuance intention and led to a more positive attitude toward AI. Our study contributes to AI literacy literature with a perspective on non-expert adults, design knowledge for an informal learning experience, including a useable IT artifact for AI literacy education, and insights into the consequences of AI literacy concerning human intentions and attitudes.

4.9 Appendix of Chapter 4

4.9.1 Appendix 4.A: AI Literacy Measurement Items

ID	Question	Answers (Multiple choice, correct answers in **bold**)	Exemplary supportive literature
1	What is the official definition of artificial intelligence (Al)?	• Al is the science and engineering of making intelligent machines, especially intelligent computer programs. • **There is no official definition of Al.**	Berente et al. (2021)
2	Which of these applications is AI?	• **A system that analyzes patterns on images of tissues to determine if cancer is present.** • A chatbot on a website that answers predefined questions.	Jussupow et al. (2021)
3	What characteristics differentiate AI from previous IT applications?	• **Ability to learn, autonomy.** • Ability to process data, usability.	Berente et al. (2021)
4	In what aspect are humans better than AI?	• **Interpersonal and social intelligence.** • Recognize patterns in a data set.	Fügener et al. (2021a), Pinski, Adam, and Benlian (2023)
5	Which of the following statements is true?	• **At the heart of an Al application is a statistical model that is refined through the use of training data.** • At the heart of modern Al application is a database containing all the necessary information.	Schuetz and Venkatesh (2020)
6	What steps do humans perform in the development process of an AI?	• **Selection of training data, choice of statistical model.** • Analysis of the training data, making a prediction.	Long and Magerko (2020)
7	An Al model always achieves the same result for the same input.	• **False.** • True.	Berente et al. (2021), Schuetz and Venkatesh (2020)
8	An Al for facial recognition can also classify traffic signs without further effort.	• **False.** • True.	Benbya et al. (2021)
9	In what applications of Al can discrimination occur through the use of Al?	• **When using Al as an HR tool.** • **When using AI to serve ads on online search platforms.**	Dastin (2018)

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ID	Question	Answers	Sources
10	What can cause discriminatory bias in an Al prediction?	• **Due to a bias in the training data.** • Through transfer of data.	Meske et al. (2020), Ng et al. (2021)
11	Key ethical aspects in the context of Al include...	• **...discrimination and transparency.** • **...privacy and spread of fake news.**	Heyder and Posegga (2021), Long and Magerko (2020)
12	Through the use of current Al technologies, the following risks arise:	• **False news reports are spread.** • Al pushes away the need for humans in the job market.	Mikalef, Conboy, et al. (2022)

Table 4.3: *AI Literacy Measurement Items*

4.9.2 Appendix 4.B: Downstream Variable Measurement Items

Variable	**Item** (1 = "Strongly disagree" to 7 = "Strongly agree")
AI usage continuance intention based on Bhattacherjee (2001)	I intend to continue using AI technology when it is offered to me.
	Using AI technology for future tasks is something I would do.
	I predict that I would use AI technology in the future when applicable.
Attitude toward AI based on Nomura et al. (2006)	I would feel uneasy if I was given a job where I had to use AI. (R)
	I feel that in the future society will be dominated by AI. (R)
	I would hate the idea that AI were making judgments about things. (R)
	I feel that if I depend on AI too much, something bad might happen. (R)
	I would feel uneasy if AI really had emotions. (R)

Table 4.4: *Downstream Variable Measurement Items*

5 Effects on Human Behavior

Title:	AI Knowledge: Improving AI Delegation through Human Enablement
Authors:	Marc Pinski, Technische Universität Darmstadt, Germany Martin Adam, Technische Universität Darmstadt, Germany Alexander Benlian, Technische Universität Darmstadt, Germany
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Abstract

When collaborating with artificial intelligence (AI), humans can often delegate tasks to leverage complementary AI competencies. However, humans often delegate inefficiently. Enabling humans with knowledge about AI can potentially improve inefficient AI delegation. We conducted a between-subjects experiment (two groups, n = 111) to examine how enabling humans with AI knowledge can improve AI delegation in human-AI collaboration. We find that AI knowledge-enabled humans align their delegation decisions more closely with their assessment of how suitable a task is for humans or AI (i.e., task appraisal). We show that delegation decisions closely aligned with task appraisal increase task performance. However, we also find that AI knowledge lowers future intentions to use AI, suggesting that AI knowledge is not strictly positive for human-AI collaboration. Our study contributes to HCI design guidelines with a new perspective on AI features, educating humans regarding general AI functioning and their own (human) performance and biases.

CCS Concepts: Human-centered computing → Human computer interaction (HCI), Collaborative and social computing; Computing methodologies → Artificial intelligence

Keywords: AI Delegation, AI Literacy, AI Education, AI Skill, Cognitive Appraisal Theory

5.1 Introduction

Human-computer interaction (HCI) researchers and practitioners agree that future workplaces and societies will rely on intense collaboration between humans and artificial intelligence (AI) rather than on the replacement of all human aspects (Benbya et al., 2021; Ebel et al., 2021; Jain et al., 2021; World Economic Forum, 2022b). When humans delegate tasks to AI based on their judgment (i.e., delegation-based human-AI collaboration), many use cases become possible compared to human-AI collaboration, where humans supervise AI decision-making. Delegation-based human-AI collaboration enables humans to use AI's performance advantages in sensitive environments, such as social media content moderation (Lai et al., 2022), or in high-stakes environments, such as medical diagnostics (Baird & Maruping, 2021; Jussupow et al., 2021; Lai et al., 2022; Milewski & Lewis, 1997; Murray et al., 2021). In these collaborations, humans can leverage AI competencies that are complementary to their own competencies, which enhances overall outcomes in specific contexts (Bansal et al., 2021; Dellermann et al., 2019; Fügener et al., 2021a; Shen et al., 2021; Tschandl et al., 2020). However, this solution, which combines human and AI strengths, has a substantial drawback: Most humans are inefficient at delegation (when they have not received dedicated training) (Fügener et al., 2021a; Milewski & Lewis, 1997; F. G. Moore, 1982; Yukl & Fu, 1999). For example, managers often incorrectly believe that they are more capable or faster at performing tasks than their subordinates (F. G. Moore, 1982). In contrast, a study of 143 CEOs in the 500 fastest-growing US companies showed that those with the ability to delegate efficiently made 33% more revenue on average (Badal & Ott, 2015). Even though appropriate delegation has clear upsides, many humans seem to suffer from delegation incapacity due to perception or social biases (Fügener et al., 2021a; Milewski & Lewis, 1997). Given the potential arising from a solution to these biases, research and practice call for more exploration of human delegation behavior (Fügener et al., 2021a; Lai et al., 2022) – a question we propose to address with the human understanding of AI's technological and social aspects: **AI knowledge**.

The HCI community had already acknowledged delegation problems before the rise of AI (Höök, 2000; Milewski & Lewis, 1997). However, AI's unique competencies, such as increased autonomy or the ability to learn, have made the topic more relevant than ever (Berente et al., 2021). A recent definition describes AI as referring to technological systems at the "frontier of computational advancements that reference human intelligence in addressing complex decision-making problems" (Berente et al., 2021). This concept (i.e., the frontier) takes shape in different systems over time, such as with medical AI diagnostic tools (C. J. Cai et al., 2019). With increasing technological capacities, HCI researchers have addressed the problems in delegation-based human-AI collaboration almost exclusively in terms of the technological advancement of AI features. Recent HCI studies have covered, for example, general AI design guidelines for human-AI collaboration (Amershi et al., 2019; Yeh et al., 2022), design principles of explainable AI (Hadash et al., 2022; Liao et al., 2020; D. Wang et al., 2019), or the framing of AI errors (Kocielnik et al., 2019). AI has improved so much technologically that if we place the decision default with the AI, the collaboration can exceed the performance of (human) delegation-based human-AI collaboration (Fügener et al., 2021a). In other words, AI can be better at delegation than humans. However, this solution is not feasible in many settings, for example, due to ethical concerns or high-stakes environments.

Technological-focused research on AI delegation has undoubtedly enhanced human-AI collaboration by optimizing AI-focused features (Bansal et al., n.d.). However, research to understand human "features" (i.e., their attributes, such as knowledge) currently seems underrepresented. We lack insights into the effects of human attributes on delegation-based human-AI collaboration. Only recently have studies started investigating the impact of some human attributes on delegation-based human-AI collaboration, such as the impact of personality traits on trust in AI (W. Cai et al., 2022). HCI research centered on human attributes, such as knowledge, skills, and abilities regarding AI, formed under the term "AI literacy" (Anton et al., 2020; Cetindamar et al., 2022; Heyder & Posegga, 2021; Long & Magerko, 2020; Ng et al., 2021; B. Wang et al., 2022). This research stream thus far primarily consists of exploratory and conceptual work. HCI research introduced and defined the term "AI literacy" by summarizing different competencies that enable evaluation, communication, and collaboration with AI (Long & Magerko, 2020).

Our empirical study focuses specifically on the knowledge aspect of AI literacy. We believe that more detailed insights into the effects of AI knowledge will open opportunities up for future research in this underexplored field and will be actionable for developers and other practitioners. For example, insights into AI knowledge might have implications for the development of AI upskilling programs for humans or for the features of the AI itself. Overall, the approach to understanding human "features," such as the necessary human knowledge for AI delegation, provides a new perspective compared to the technological-driven default approach in the research field.

To determine how AI knowledge affects delegation-based human-AI collaboration, we first investigate what determines AI delegation. Based on cognitive appraisal theory and prior HCI delegation work, we presume that “task appraisal” is decisive for AI delegation (Lazarus & Folkman, 1984; Milewski & Lewis, 1997). Task appraisal refers to the twofold human assessment of how suitable a human (human-fit appraisal) or an AI (AI-fit appraisal) is for a particular task based on their (human) or its (AI) competencies (Folkman, 2013). Then, we investigate how AI knowledge affects the relationship between task appraisal and AI delegation and the relevant outcomes, such as performance. Research on (non-AI) technology knowledge has demonstrated how human knowledge could affect human-technology relationships (Bassellier et al., 2015). Therefore, we believe that AI knowledge moderates the relationship between task appraisal and AI delegation; that is, it aligns AI delegation decisions with the assessment of who (AI vs. human) is more suitable for the task. The more knowledgeable humans are regarding AI, the more they will align their AI delegation decisions with their task appraisals. Furthermore, efficient delegation is predominantly relevant when the underlying task is difficult for humans, yet AI and humans have complementary competencies. Therefore, our first research question (RQ1) states:

> *How do task appraisal and AI knowledge affect human delegation behavior in human-AI collaborations under challenging tasks?*

The HCI community views AI knowledge as exclusively positive, empowering humans in collaboration with AI (Long & Magerko, 2020; Ng et al., 2021). On the other hand, information processing studies point out that more information is not always better in complex contexts and is sometimes even harmful, for example, by causing information overload (Cram et al., 2020; Simon, 1990). AI is a complex context in which we still need to explore the specific effects of AI knowledge. To uncover the potentially diverse effects of AI knowledge, we investigate the outcomes of delegation-based human-AI collaboration from two perspectives: performance (objective perspective) and the human intention to use AI (subjective perspective). A user’s intention to continue using AI in the future is a crucial metric for HCI research or when designing AI (Bhattacherjee, 2001; Hu et al., 2021; M. Lee & Park, 2022; Sun et al., 2021; Thong et al., 2006). When users do not intend to continue using AI, any human-AI collaboration loses the chance of achieving its goal. Employing the established concept of human “AI usage continuance intention” (AUCI), we investigate how AI knowledge affects human attitudes (subjective perspective). On the other hand, performance (objective perspective) is an outcome of great importance to practitioners (e.g., developers) when designing AI (Bansal et al., 2021). Therefore, we formulate a second research question (RQ2) as follows:

> *How do AI knowledge and delegation behavior impact the performance of human-AI collaborations and the AUCI of interacting humans?*

We designed a between-subjects experiment (two groups, n = 111) to answer our research questions. In this experiment, a control group solved difficult image classification tasks with the option of delegating to an AI. We enabled a treatment group with specific AI knowledge and compared its AI delegation behavior and task appraisal to the control group. We chose image classification as the task context for our study because it is a model case for AI, as processing such data with conventional technology is impossible (C. J. Cai et al., 2019). Prior research has also shown that image classification benefits from the collaboration of humans and AI due to complementary competencies (Fügener et al., 2021a). Furthermore, there are many scenarios, such as social media content moderation or medical diagnoses, where it is not feasible to set the default with the AI, which requires an investigation into the "human features," namely, AI knowledge (C. J. Cai et al., 2019; Jussupow et al., 2021; Stjernfelt & Lauritzen, 2020; Topol, 2019). This paper makes the following contributions:

- We show that *task appraisal can explain AI delegation behavior for humans enabled with AI knowledge.* We further detail how task appraisal consists of AI and human task appraisals. The finding's main implication is an extension of HCI design guidelines for AI with a new perspective on AI design features focused on educating humans regarding their own (human) performance and biases.
- We explain that *AI knowledge can improve human-AI collaboration performance by aligning AI delegation behavior more closely with task appraisal.* This finding implies that AI knowledge as a human "feature" enhances performance, as prior HCI research has shown for technological AI features. However, human AI knowledge can circumvent some of the downsides of AI features and constitutes an alternative for performance enhancement.
- We identify that *AI knowledge can reduce AI usage continuance intention* (AUCI). This result calls into question the so far exclusively positive view of AI knowledge (and AI literacy). It implies that further research is needed to better understand AI knowledge's desired and undesired effects on human-AI collaboration.

5.2 Related Work

5.2.1 Cognitive Appraisal Theory and Delegation within HCI

Humans confronted with a stimulus, such as a task, can express various behaviors, including avoidance, compliance, or deviance (Bhattacherjee et al., 2017). Cognitive appraisal theory explains these human coping responses (Beaudry & Pinsonneault, 2005; Folkman, 2013). It introduces two factors that determine the coping strategy of a human confronted with a challenging or unfamiliar situation: the perception of the situation and the attributes of the human (Lazarus & Folkman, 1984). The latter includes the human's knowledge, beliefs, or values (Lazarus & Folkman, 1984). Within this theoretical framework, Folkman defines "appraisal" as evaluating how a situation evolves in relation to a human's goals (Folkman, 2013). In other words, humans assess a task (situation) and their knowledge (attribute) to pursue their goals. Coping also includes the appraisal of different coping options and the choice of a coping strategy to pursue one's goals (Folkman, 2013).

When confronted with a task (stimulus), a potential coping response might be delegation to a subordinate. Since different tasks necessitate tailored coping strategies (Folkman, 2013), delegation research adds a meaningful perspective to specify the factors introduced by cognitive appraisal theory for delegation. In general, "delegation" refers to transferring rights and responsibilities for a task from one human or entity to another (Baird & Maruping, 2021; Milewski & Lewis, 1997). The economic and management literature has already widely researched delegation: while one stream is concerned with the underlying logic of rational choice under certain conditions, going back to the principal-agent problem (Holmström, 1979), a second stream focuses on the factors that predict a human's delegation decision (Leana, 1986, 1987). Delegation research distinguishes between three determinants of a delegation decision: attributes of the delegating human, perceptions of the subordinate's attributes, and situational characteristics (Leana, 1986; Yukl & Fu, 1999). These determinants make cognitive appraisal theory specific to delegation. Most notably, the perception of the situation breaks down into perceptions of the subordinate and other situational characteristics (e.g., the task) (Baird & Maruping, 2021). Therefore, in the delegation context, "task appraisal" refers to a human's assessment of the fit of their own attributes vs. a subordinate's attributes for a given task.

The HCI context introduces technology-based agents to such a delegation relationship (Milewski & Lewis, 1997). Technology-based agents that have been researched in the delegation context include, for example, IoT devices (Verame et al., 2018), software programs (Milewski & Lewis, 1997; Schulte et al., 2016), or aircraft computers (Navarro et al., 2021; Tokadlı et al., 2021; Xie et al., 2019). To date, HCI scholars have investigated the collaborations of humans and technology-based agents, with a clear focus on the technological features of the technology-based agent ("subordinate"). For example, studies that found that managers tend to delegate less than what would optimize outcomes provided design-oriented solutions focused on the features of technology-based agents (Milewski & Lewis, 1997; F. G. Moore, 1982). These solutions include, among others, design guidelines to "increase the observability of the agent's behaviors," aiming to increase trust in the technology-based agent (Milewski & Lewis, 1997; F. G. Moore, 1982).

5.2.2 Human-AI Collaboration

The rise of AI has further increased delegation's significance in the relationship between humans and technology-based agents (Adam et al., 2023; Baird & Maruping, 2021; Dolata et al., 2021; Schuetz & Venkatesh, 2020). Since the meaning of the term "AI" diffused due to the enormous traction it generated across disciplines (Ågerfalk, 2020), in this paper, we have adopted the view of AI as technology at the "frontier of computational advancements" (Berente et al., 2021). Currently, three facets characterize these technologies: autonomy (capacity to act on its own), learning (ability to improve over time), and opacity (understandable only to a select audience or nobody) (Berente et al., 2021). These facets have varying significance in different AI technologies. For example, transparent and interpretable models (e.g., decision trees) behave differently from opaque models (e.g., neural networks) (Thiebes et al., 2020). Many AI technologies have a significantly greater capacity to act independently than prior technologies, such as self-driving cars (Rao & Frtunikj, 2018) or robotic traders (Cao, 2020). Increased autonomy leads to two developments that make AI particularly interesting for delegation: AI can now assume tasks that were previously exclusively handled by humans, such as medical diagnostics (Jussupow et al., 2021; Topol, 2019), and agentic AI itself can now take on the role of the delegator, which can lead to superior results in specific tasks (Baird & Maruping, 2021; N. Carroll, 2021; Fügener et al., 2021a). These developments challenge core assumptions held in HCI for decades, such as exclusive human agency, requiring a reassessment of collaboration between humans and technology (Schuetz & Venkatesh, 2020). Although AI might possess the capacity to act autonomously, there are still vibrant discussions about where and how it should do so (Mikalef, Conboy, et al., 2022). The literature agrees that AI will likely not replace humans in all their functions; rather, it will enhance their work in specific areas (Dolata et al., 2021; Engel et al., 2022; Jain et al., 2021; Willcocks, 2020). Improving the emerging human-AI collaborations remains one of the most discussed topics in the HCI community.

HCI researchers have approached human-AI collaboration in various domains to gain insights that translate into actionable improvements for human-AI collaboration. For example, studies have employed (video) games to show that human-AI collaboration can achieve superior performance as a team (M. Williams et al., 2016) or to identify design features enhancing performance (Liang et al., 2019; Zhu et al., 2021). Such design recommendations include AI communication features that promote a human-like appearance (Liang et al., 2019) or purposefully playful interactions with AI (Zhu et al., 2021). However, introducing AI into human teams can also harm performance by lowering the perceived team cognition (i.e., the perceived shared ability to use knowledge) (McNeese et al., 2021). These ambiguous findings necessitate balancing AI's performance and its adverse effects. Therefore, the discipline has produced different frameworks to structure specific aspects of human-AI collaboration, enabling informed choices for the usage and design of AI (Amershi et al., 2019; Lubars & Tan, 2019; Teodorescu et al., 2021; Vössing et al., 2022). Regarding AI delegation, for example, Lubars and Tan proposed a framework with four dimensions determining the human preference to delegate specific tasks: intrinsic motivation, human trust, task difficulty, and associated risk (Lubars & Tan, 2019). In addition to human preference, researchers further agree that human-AI collaboration must match ethical standards (Dolata et al., 2021). Therefore, a viable design criterion is, for example, the "fairness difficulty" of decisions, defined as the number of fairness criteria deciders must optimize with their choices (Teodorescu et al., 2021). An example of a high fairness-difficulty decision made by a human, which an AI could support, is a hiring decision. The degree of fairness difficulty can then help to decide whether an AI design should include human oversight elements rather than "blind" reliance.

5.2.3 Emergent Work on AI Knowledge

Human knowledge of technology is not a new concept. The IT competence literature distinguishes between the two core competence components of knowledge and experience (Bassellier et al., 2003, 2015). IT experience describes tacit competence relating to "knowledge" gained through personal experience, which cannot easily be codified or transmitted (Nonaka, 1994). On the other hand, IT knowledge describes explicit knowledge, which can be codified in a formal language and transmitted (Nonaka, 1994). Within this framework, different technology competence concepts developed under the term "literacy," such as digital literacy (Eshet-Alkalai, 2004; A. Nguyen et al., 2020) or data literacy (Kerpedzhiev et al., 2020; Someh et al., 2019). Based on the developments explored above, such as AI invalidating core HCI assumptions, the community expressed the need to develop new literacy concepts to accommodate the specificities of AI (Long & Magerko, 2020; Tarafdar et al., 2022). Therefore, Long and Magerko introduced the term "AI literacy" (Long & Magerko, 2020). They defined AI literacy as competencies enabling evaluation, communication, and collaboration with AI (Long & Magerko, 2020). Following the tradition of IT competence research, we view AI knowledge as a core element of the broader and recently coined concept of AI literacy.

Despite increasing AI literacy studies, HCI research is still developing. Most of the current work is exploratory and conceptual. For example, studies have identified critical or sociocultural competence as part of AI literacy (Anton et al., 2020; Cetindamar et al., 2022; Heyder & Posegga, 2021; Süße et al., 2021), developed an AI competence complexity hierarchy (Ng et al., 2021), or set out to establish measurement tools for AI literacy (B. Wang et al., 2022). Until today, research has portrayed AI literacy as a concept with exclusively positive impacts. Although most studies focus on the technological elements of AI literacy, the literature acknowledges that AI literacy comprises competencies relating to AI and humans (Anton et al., 2020; Cetindamar et al., 2022; Heyder & Posegga, 2021). In other words, AI literacy, and hence AI knowledge as its element, has a social (human) and technological (AI) component. Conceptualizations of AI literacy include competencies such as "AI's strengths and weaknesses" (technological component) but also "the human role in AI" (social component), reflecting both components. Therefore, AI knowledge must include what an AI can and cannot do, but at the same time, also what the human role in the interaction is and what humans can and cannot do (Long & Magerko, 2020).

5.3 Research Model and Hypotheses

We developed a research model based on cognitive appraisal theory (Folkman, 2013) and structured it along an AI delegation process in human-AI collaboration (Figure 5.1). During task appraisal, humans collaborating with AI assess how suitable a given task is for humans (human-fit appraisal) and AI (AI-fit appraisal), which affects their AI delegation behavior (H1a, H1b). Then, we propose a moderation effect of AI knowledge on each introduced effect, meaning that more AI knowledge leads to AI delegation behavior that is more aligned with task appraisal (H2a, H2b). If someone appraises a task as fitting for a human, they should retain the decision, while if they appraise it as fitting for an AI, they should delegate. Thereby, we intend to shed light on the mechanism that explains why and how AI knowledge impacts the appraisal-delegation relationship in human-AI collaboration. Finally, we investigate whether delegation behavior and AI knowledge improve the outcomes of the "performance of human-AI collaboration" (H3a) and AUCI (H3b). The following subsections elaborate on each proposed relationship, as shown in Figure 5.1.

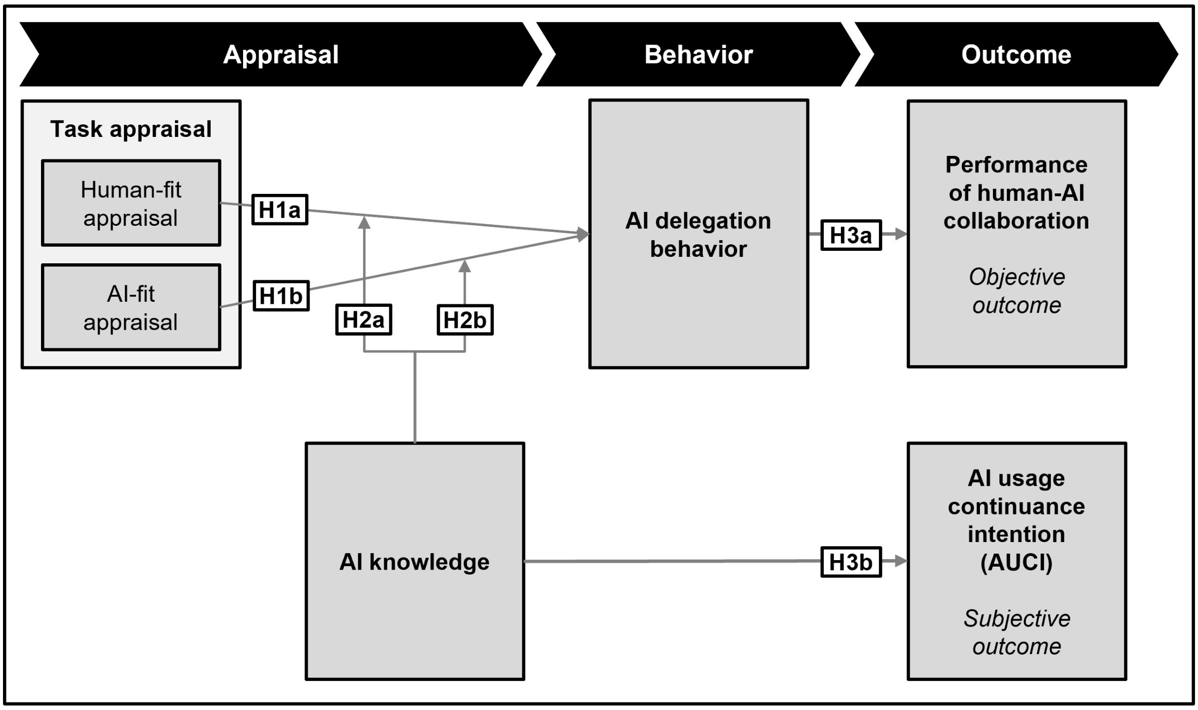

Figure 5.1: *Research Model*

5.3.1 Effects of Task Appraisal on AI Delegation Behavior

Cognitive appraisal theory states that human attributes and situational characteristics drive coping responses (Lazarus & Folkman, 1984). Delegation research details the determining factors by specifying the delegator's attributes, their perceptions of the subordinate's attributes, and the situational characteristics (e.g., task difficulty) as drivers of coping responses (Leana, 1986; F. G. Moore, 1982). Prior HCI research has shown how individual attributes, such as personality traits, impact attitudes toward AI

(W. Cai et al., 2022) or how perceptions of subordinates' competencies affect delegation behavior (Leana, 1986). Based on cognitive appraisal theory and prior delegation research, we hypothesize that a twofold task appraisal mechanism determines the AI delegation decision. This twofold mechanism consists of AI-fit appraisal and human-fit appraisal. In other words, humans assess the fit of an AI and themselves with the underlying task to make their delegation decision. Given the performance objective, the more a task suits a human (human-fit appraisal), the less it should be expected that the human will delegate the task. Delegation to an AI that can potentially be wrong only lowers performance expectations if humans can solve the task alone. Therefore, we expect the human-fit appraisal to negatively impact delegation behavior. On the contrary, if a human judges a task as more suited for an AI (AI-fit appraisal), we expect humans to use the AI's complementary competencies and delegate the task to improve overall performance. Therefore, we expect AI-fit appraisal to positively impact delegation behavior. In summary, we hypothesize the following:

H1a: High (vs. low) human-fit appraisal decreases AI delegation behavior.

H1b: High (vs. low) AI-fit appraisal increases AI delegation behavior.

5.3.2 Moderation Effect of AI Knowledge

Cognitive appraisal theory suggests that different human attributes (e.g., knowledge) influence the appraisal of a task. While prior delegation research shows that humans tend to delegate much less than would be optimal (Milewski & Lewis, 1997), many examples also show that humans can learn to become better delegators and thus achieve superior results (Badal & Ott, 2015; F. G. Moore, 1982). Emergent AI literacy research shows that AI technology, compared to non-AI technology, is qualitatively different and that specific AI knowledge is needed (Berente et al., 2021; Long & Magerko, 2020). Based on prior delegation and AI literacy research, we hypothesize that AI knowledge is a critical human attribute that moderates the relationship between task appraisal and AI delegation behavior. Specifically, we argue that AI knowledge strengthens the relationship between task appraisal and AI delegation behavior. We further claim that AI knowledge impacts both the influence of human-fit appraisal and AI-fit appraisal. Strengthening the relationship between task appraisal and AI delegation behavior (i.e., moderation) means that more AI knowledge leads to AI delegation behavior that is more aligned with task appraisal. AI knowledge makes humans more efficient delegators because they allocate tasks according to actual assessed competencies. Internally, they are thus behaving more consistently. Like H1a and H1b, we ground this hypothesis in prior research, which states that the perception of the subordinate (AI) influences delegation behavior (Leana, 1986). With more knowledge about AI, the perception of AI reflects the reality of AI more precisely. Furthermore, prior research suggests that a lack of meta-knowledge (i.e., knowledge about one's knowledge) is an inhibitor of efficient delegation (Fügener et al., 2021a; Milewski & Lewis, 1997). When humans lack meta-knowledge, they overestimate their abilities and delegate too little (Fügener et al., 2021a). Therefore, we propose that AI knowledge addresses this shortcoming by increasing awareness of one's own competencies. In summary, when a given task is difficult, AI knowledge is expected to enable humans to recognize their impairments and the superiority of AI, which results in a stronger relationship between task appraisal (human fit and AI fit) and AI delegation behavior. Therefore, we hypothesize the following:

> H2a: AI knowledge amplifies the effect of human-fit appraisal on AI delegation behavior, such that human-fit appraisal has a stronger effect on delegation behavior when AI knowledge is high (vs. low).
>
> H2b: AI knowledge amplifies the effect of AI-fit appraisal on AI delegation behavior, such that AI-fit appraisal has a stronger effect on delegation behavior when AI knowledge is high (vs. low).

5.3.3 Effects on Outcomes of Human-AI Collaboration

Apart from the change in AI delegation behavior, it is relevant for HCI academics and practitioners to understand the effects of AI knowledge on outcomes of human-AI collaboration, including objective outcomes (e.g., performance) and subjective outcomes (e.g., AUCI). Practitioners will only use AI knowledge concepts if their impact on the relationship between task appraisal and delegation leads to better task performance or improves human attitudes, such as AUCI.

Prior human-AI collaboration research has shown that humans and AI possess complementary competencies (Fügener et al., 2021a). If a particular task is difficult for humans, increasing delegation to an AI with complementary competence should raise overall performance. On the other hand, if a task is easy for humans and they achieve high accuracy, delegation to an AI with complementary competencies might only harm performance due to the potential errors of the AI. Hence, we hypothesize that delegation to AI positively impacts performance if the underlying task is difficult for humans.

> H3a: High (vs. low) AI delegation behavior increases task performance if the task is difficult for the interacting human.

HCI research is also particularly interested in the subjective outcomes of human-AI collaboration (Jain et al., 2021; Thong et al., 2006). Human beliefs and attitudes about AI are crucial factors in facilitating human-AI collaboration (Choung et al., 2022). As such, AUCI expresses the user's willingness to use AI in the future (Hu et al., 2021; M. Lee & Park, 2022; Sun et al., 2021). Prior research has shown that, for example, competence perceptions of an AI positively influence AUCI (Hu et al., 2021). Within the introduced theoretical framework, the perception of the subordinate (i.e., the AI) expresses AI competence perceptions. AI knowledge educates humans, among other aspects, about AI's competencies and drawbacks. A more comprehensive picture of AI should enable a human to better judge when it is beneficial to use AI. Therefore, AI knowledge should positively impact the intention of humans to use AI when it is applicable (i.e., their AUCI). In summary, we derive the following:

> H3b: High (vs. low) AI knowledge increases the AI usage continuance intention (AUCI) of the interacting human.

5.4 Delegation Experiment

We used a between-subjects experiment (AI knowledge enablement condition vs. control group) to test our research model, allowing for the targeted manipulation of AI knowledge and control of environmental and task-related influences. We implemented our research design as an online experiment with four phases (Figure 5.2): pre-study questionnaire, AI knowledge enablement, AI delegation tasks, and post-study questionnaire. First, both groups (treatment and control) received information about the procedure and completed a pre-study questionnaire recording the control variables. Next, only the treatment group received AI knowledge enablement, thus increasing their AI knowledge. Both groups then solved eight tasks with an AI delegation option in a human-AI collaboration setup. The experiment closed with a post-questionnaire recording the participants' AUCIs and the sample statistics. In the following section, we explain in detail the core steps of the experiment, that is, AI knowledge enablement (Subsection 5.4.1) and the AI delegation task (Subsection 5.4.2). Furthermore, we expand on the measures (Subsection 5.4.3) and participants (Subsection 5.4.4) at the end of the section.

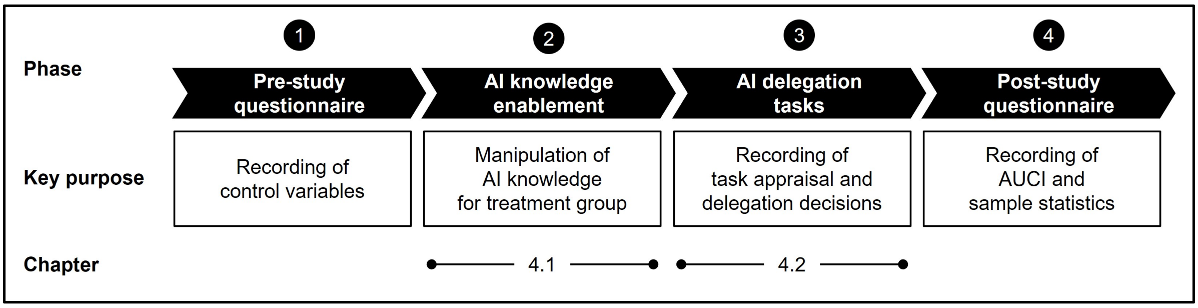

Figure 5.2: *Experimental Design*

5.4.1 AI Knowledge Enablement

We increased the treatment group's AI knowledge in our experiment to assess its impact on the appraisal–delegation relationship and AUCI. Participants in the treatment group received information (AI knowledge) on the strengths and weaknesses of both parties in the human-AI collaboration (i.e., human and AI). We categorized AI knowledge into human and AI components to reflect the hypothesized twofold task appraisal (Figure 5.3). We specified the AI knowledge enablement for the chosen task context of image classification (see below for a detailed discussion concerning the task context). Each AI knowledge component from the enablement builds on relevant literature (Table 5.1). We ensured balanced information on the strengths and weaknesses of humans and AI because the subjects needed to comprehend that image classification was a task that benefited from the human-AI collaboration.

After reviewing the information, participants in the treatment group had to restate the key points of the presented information by summarizing them in two sentences in a mandatory open-answer question. We implemented the question to ensure that participants had appropriately understood the information. Furthermore, educational research shows that summarizing information in one's own words is a highly effective learning strategy (King, 1992). For example, one participant answered the mandatory summary question with the following statement:

> *"AI's greatest advantage is its ability to utilize large masses of datasets with objective reasoning. In contrast, AI's greatest weakness is in its lack of ability to work in a system not reliant on patterns or outside of a controlled environment."*

Additionally, we implemented a manipulation check to ensure that the AI knowledge enablement worked. The participants received an identical set of eight questions about the presented AI knowledge before and after the enablement phase (see Appendix 5.A for the questions [Table 5.10]). We tested for a significant increase in the averaged answers of our manipulation test (i.e., an increase in AI knowledge). Therefore, we can confirm that the treatment significantly increased AI knowledge in the treatment group (two-sided t-test, $p < .05$).

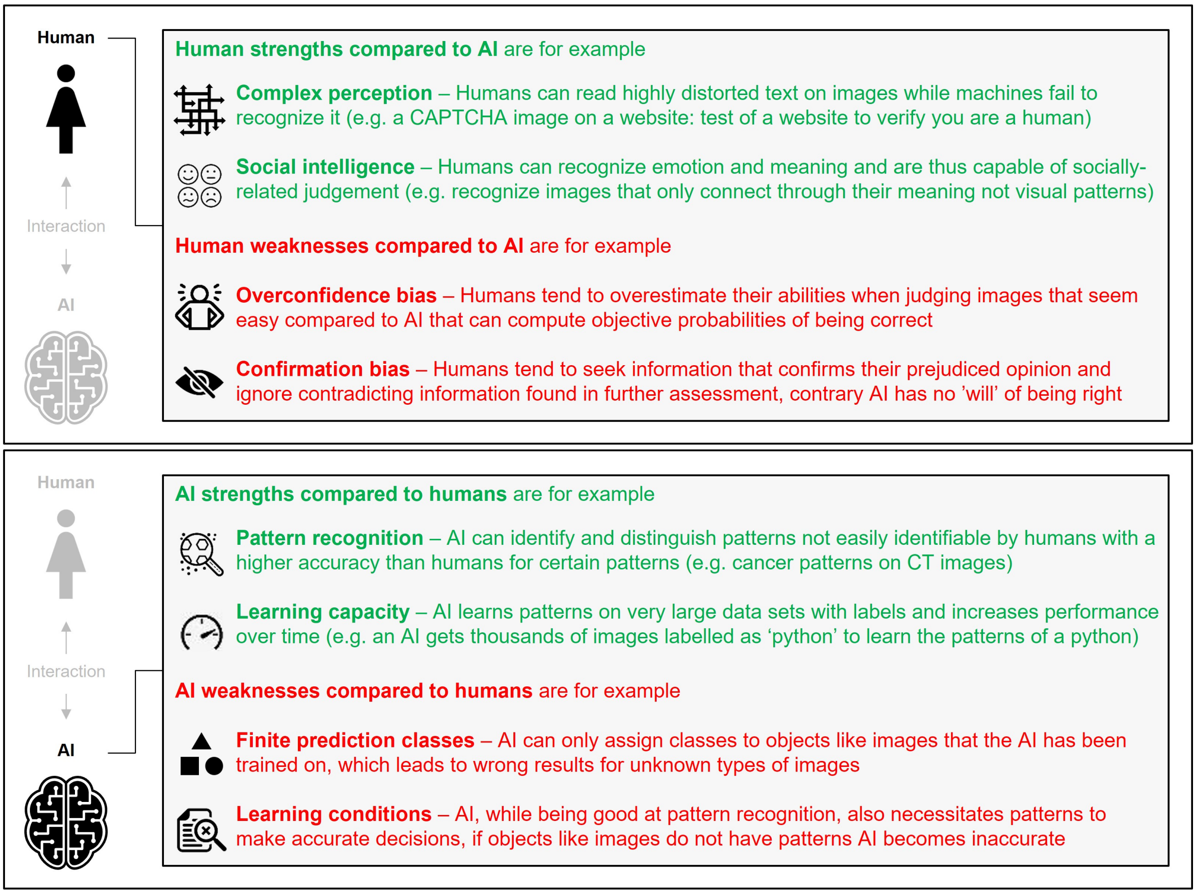

Figure 5.3: *AI Knowledge Enablement Treatment*

5.4.2 AI Delegation Task

5.4.2.1 Image Classification as the Task Context

Following prior AI delegation research, we chose the task context of image classification (Fügener et al., 2021a, 2021b; Jussupow et al., 2021). Image classification is a model case for using AI, with much research demonstrating the potency and value that AI has across different contexts, such as medicine (C. J. Cai et al., 2019; Jussupow et al., 2021; Topol, 2019), autonomous driving (Rao & Frtunikj, 2018), or facial recognition (X. Ding

	Humans	AI
Strengths	Humans are superior in recognizing specific types of images, for example, those which necessitate social intelligence or highly complex perception (Fügener et al., 2021a; Willcocks, 2020).	AI is superior in recognizing specific types of images, for example, those with distinctive patterns or objects (Fügener et al., 2021a; Jussupow et al., 2021).
Weaknesses	Humans are subject to certain biases, and hence, they are inferior in recognizing specific types of images (Kahneman & Tversky, 1984; Tversky & Kahneman, 1974).	AI is subject to certain technical conditions, and hence, it is inferior in recognizing specific types of images (Berente et al., 2021; van Giffen et al., 2022).

Table 5.1: *Key Messages of AI Knowledge Treatment Per Category Conveying That Humans and AI Have Complementary Competencies in Image Classification*

et al., 2019). Specifically, image classification is suited to studying delegation behavior in human-AI collaboration for two reasons: the complex social context in particular domains and the complementary competence of humans and AI.

Real-world image classification tasks frequently occur in complex social contexts, necessitating human consideration of aspects beyond performance, such as ethical standards, legal requirements, the risks involved, or human preferences (Lubars & Tan, 2019; Murray et al., 2021; Teodorescu et al., 2021). These aspects often make it impossible to find general solutions to the delegability of image classification tasks. For example, social media content moderators must often make edge-case decisions regarding the appropriateness of images on social networks, which AI can barely distinguish (Lai et al., 2022; Stjernfelt & Lauritzen, 2020). They must balance ethical standards and human rights, such as free speech, with the vast number of images they need to classify, necessitating efficient classification. In summary, the social context of image classification tasks makes them a relevant task type to study regarding AI delegation.

Research also shows that human-AI collaborations can achieve higher performance in image classification than humans or AI alone (Fügener et al., 2021a; Tschandl et al., 2020). This means that image classification is a task context in which the complementary competencies of humans and AI exist, justifying delegation-based collaboration to improve performance. A study on the widely used ImageNet dataset showed that human baseline performance increased through the option to delegate to AI (Fügener et al., 2021a). However, only a human-AI collaboration placing the delegation option with the AI beat the AI baseline performance. The AI with the delegation option significantly outperformed by following a rule to delegate to a human when its accuracy fell below average human accuracy. This finding shows the value of human-AI collaboration in image classification. It also identifies substantial room for improvement in accuracy when humans are delegating (.74) vs. when AI is delegating (.87). In summary, image classification often appears in a complex social context that necessitates efficient human judgment, but it can benefit from complementary competence through delegation.

5.4.2.2 Image Classification Task Data

We used the ImageNet dataset of 2017 (latest version, Stanford Vision Labs, 2022) as the source of images for the classification tasks, thereby also following prior delegation research on image classification (Fügener et al., 2021a, 2021b). The dataset is publicly available and widely recognized for training and testing image classification models, enabling future research to build on it and compare its results. We chose the dataset because it contains various image classes comparable to the social media context explored above as a domain in which image classification is applicable. The image classes include, for example, animals (e.g., multiple breeds of dogs, cats, or snakes), humans (e.g., baseball players, scuba divers, or grooms), human-crafted objects (e.g., vehicles, musical instruments, or technological devices), food (e.g., pretzels, cauliflower, or burgers), or landscapes (e.g., mountains, deserts, or coral reefs). The image class variety reflects what a social media content moderator might need to assess, as all these image classes are comparable to what one might post on social media (e.g., vacation pictures or images of pets). Humans easily distinguish a dog from a technological device (Figure 5.4: class one vs. four). However, it is more challenging to distinguish dog breeds from each other if one is not a subject expert (Figure 5.4: class one vs. two vs. three). A social media content moderator having to distinguish between forbidden nudity vs. allowed art or discriminating images vs. personal opinion similarly necessitates placing their attention on minor features that make a difference in classification. Furthermore, research confirmed, specifically for the ImageNet dataset, that complementary human and AI competence exists and maximizes performance (Fügener et al., 2021a).

5.4.2.3 Implementation of AI Delegation Tasks

Both groups solved eight image classification tasks in the experiment's AI delegation task phase. We presented the participants in each task with an image and five image classes as answer options, represented by ten sample images (Figure 5.4). The participant's goal was to classify the image into the correct class, with or without delegating to the AI. We chose the number of tasks to balance the time required for the experiment and the number of delegation decisions per participant (the average completion time was 7.9 minutes).

We used Google's Inception V3 model as an AI to select the top five image class predictions as answer options for each task (Google, 2022). The model is trained on the ImageNet dataset and achieves an accuracy of 78.1%. We always included the correct answer option, even when the Inception V3 model did not find the answer within its top five predictions. To ensure the high task-difficulty condition (according to RQ1), we first pre-tested the difficulty for humans of 50 randomly sampled images from the ImageNet dataset in a focus group. We selected the eight most difficult images for the main experiment. To verify the condition, we recorded the participant's classification decisions regardless of their delegation decisions. Requiring participants to always make a classification decision also ensured that participants did not just delegate decisions to avoid the effort associated with answering the tasks themselves. We compared the overall and per-image performance in the experiment to the known average difficulty of the data. As a result, all of the included images sufficed regarding our complexity criteria (Threshold: maximum of 50% average human accuracy, compared to 72% known average human accuracy on the total dataset, Fügener et al., 2021a). The average correct assignment was 28%, falling at the more complex end of the ImageNet dataset (Fügener et al., 2021a). The correct assignment per image ranged from 15% to 46% (see Appendix 5.C for classification performance details [Table 5.13]).

The participants received a fixed reward for the study and were additionally financially incentivized to maximize the share of correct answers. We informed the participants that if they chose to solve the task themselves, their response counted for their score, and if they decided to delegate to the AI, the AI's decision counted for their score. Furthermore, we informed the participants that the top 40% in the study would receive a 25% bonus payment in addition to their fixed payment. The average reward per participant was .83 USD, implying an hourly wage of 6.38 USD, given the average experiment duration. Thereby, the reward lies above the Amazon Mechanical Turk (MTurk) average (3.13 USD/h), according to HCI research (Hara et al., 2018), and also slightly above other image classification studies (Fügener et al., 2021a). We implemented this measure to ensure that the participants exerted reasonable effort while making their delegation decision and followed their objective to maximize the share of correctly assigned images as a human-AI collaboration, regardless of whether they or the AI made the decision.

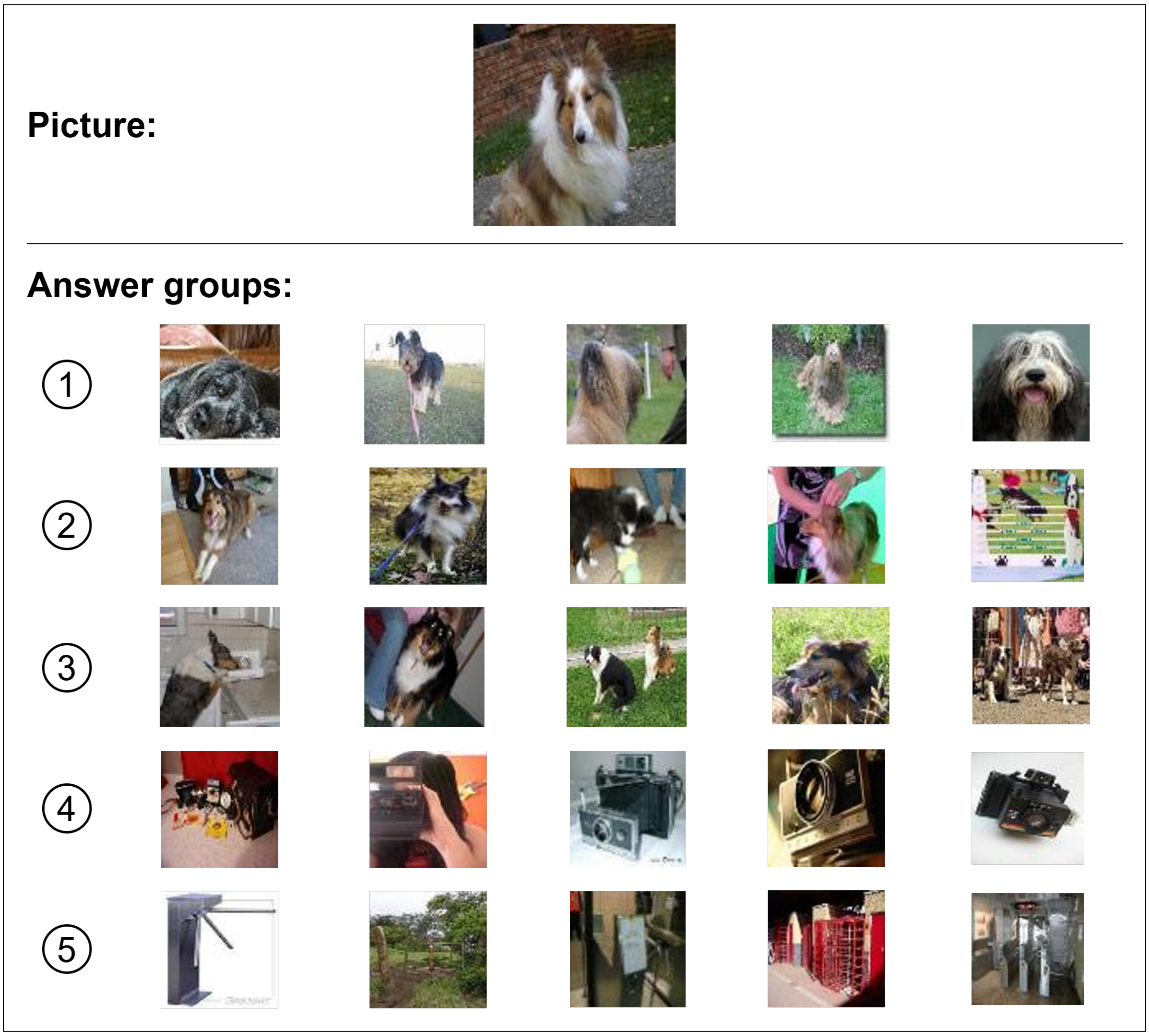

Figure 5.4: *Image Classification Task (Example)*

5.4.3 Measures

In the following, we expand on the measurement of each variable from our research model (Figure 5.1), apart from AI knowledge, which we explored in detail in (subsection 5.4.1). Additionally, we introduce the control variables. Depending on availability within the literature, we either used established scales, modified established scales to ensure AI specificity, or developed items to measure our constructs. We provide a variable validation of all deployed scales.

Task appraisal: We measured the task appraisal with two self-developed items based on 7-point Likert-type scales. One item assessed the human fit for a task, and one item assessed the AI fit for the same task. The items specifically asked how much the participants agreed that the task suited human and AI competencies (see Appendix 5.A for the items [Table 5.7]). They evaluated this fit for each of the eight tasks. Finally, we averaged the task appraisal across all solved tasks.

AI delegation behavior: We recorded the delegation decisions of each of the eight tasks and viewed each task as a repetition of a difficult image classification task. Therefore, we averaged each subject's delegation decisions to measure delegation behavior. In other words, AI delegation behavior expresses the share of delegated decisions per participant.

Performance of human-AI collaboration: The share of correctly classified images measured the performance of the human-AI collaboration (objective outcome). Whether the human's or the AI's decision counted depended on the participant's delegation decision.

AI usage continuance intention (AUCI): Technology usage continuance intention is an established concept in HCI research (M. Lee & Park, 2022). Therefore, we leveraged an established technology continuance intention scale (Bhattacherjee, 2001; Thong et al., 2006). To measure AUCI (subjective outcome), we specified the wording of the items for AI technology (see Appendix 5.A for the items [Table 5.9]).

Control variables: Cognitive appraisal theory states two factors that determine a human response: the human's attributes and their perception of a situation. We controlled the situation (external factors) through our experimental setup, that is, task difficulty and type. Regarding human attributes (internal factors), we implemented several control variables. Following the definition above, AI literacy consists of AI knowledge and experience. In our experiment, we manipulated only AI knowledge and therefore needed to control for AI experience. This design choice rests on AI knowledge being actively influenceable in real-world settings, which makes it more relevant. Since no established scale was available in the literature, we developed a short scale to measure AI experience (see Appendix 5.A for the items [Table 5.8]).

Additionally, we controlled for other personal factors that could potentially impact AI delegation behavior, such as general technology commitment and negative attitudes toward AI. Prior research on (non-AI) technology suggests that higher general commitment and negative attitudes toward technology likely impact how willing one is to delegate a task to an AI (Leana, 1986; Milewski & Lewis, 1997; Neyer et al., 2016; Nomura et al., 2006). We deployed a short version of an established "technology commitment scale" (Neyer et al., 2016) and adapted an established "negative attitude toward robots scale" (Nomura et al., 2006) regarding AI. Within the latter scale, we replaced the term "robot" with "AI."

Validity: We evaluated the validity of all deployed variables according to established scale-evaluation guidelines (MacKenzie et al., 2011; Podsakoff et al., 2016). We tested each scale's item loadings, internal consistency, composite reliability, and discriminant validity. Overall, the applied tests support the validity of the scales used. All items had significant ($p < .001$) item loadings above .60 (see Appendix 5.B [Table 5.11]). The data supports internal consistency and discriminant validity. Cronbach's alpha and the composite reliability exceed the threshold of .70, and the average variance extracted exceeds the threshold of .50 for all variables (Fornell & Larcker, 1981) (see Appendix B.2 [Table 5.12]).

5.4.4 Participants

Following prior image classification work, we chose MTurk to collect our data (Fügener et al., 2021a). MTurk offers the advantage that workers regularly perform image classification on the platform (Amazon, 2017). Therefore, we can reasonably assume that the participants are at least familiar with similar tasks, which increases the data quality of the sample. In total, 167 participants took part in our study. We implemented four attention checks and excluded every participant who did not meet a threshold of at least three to ensure that the participants exerted reasonable effort. After excluding invalid answers, our sample size totaled 111 valid responses, with 55 subjects in the control group and 56 in the AI knowledge treatment group. This implies 888 delegation decisions since each participant solved eight tasks. The participants were, on average, 34.2 years old. The sample consisted of 39.6% female and 60.4% male participants (no one chose "other" as their gender). Of the participants, 86.5% had a university degree, and 6.3% had completed an apprenticeship, leaving 7.2% with a high school diploma or lower degree. The sample also represented a broad range of occupational fields. The top five were information and communication technology (26.1%), manufacturing (12.6%), health and social work (10.8%), financial and insurance services (7.2%), and education and training (7.2%). Considering all the descriptive metrics, we deemed our sample representative and appropriate for evaluating the effects of AI knowledge and task appraisal in the AI delegation context.

5.5 Results

We analyzed the collected data using the statistical software R (version 4.2.0). Specifically, we used the established library "lavaan" (version 0.6-11) to create multiple structured equation models (SEMs) to test our hypotheses. The unit of analysis is the individual.

5.5.1 Effects on Delegation Behavior

First, we tested H1a and H1b. These hypotheses stated that we expected to find a negative effect of human-fit appraisal (H1a) and a positive effect of AI-fit appraisal (H1b) on AI delegation behavior (i.e., the delegation rate). We created an SEM to test the hypothesis for the total dataset (Table 5.2, Model 1). We find both coefficients, human-fit appraisal (negative) and AI-fit appraisal (positive), to be in the expected direction and at a significant level. Therefore, we conclude that the data support hypotheses H1a and H1b.

DV: Delegation rate	**Model 1** Total dataset (n = 111)			**Model 2** Only control group (n = 55)			**Model 3** Only AI knowledge Treatment group (n = 56)		
Variable	Coef.	SE	t-value	Coef.	SE	t-value	Coef.	SE	t-value
Human-fit appraisal	(.101)	.042	(2.432) *	(.082)	.076	(1.081) n.s.	(.099)	.048	(2.077) *
AI-fit appraisal	.082	.042	1.959 +	.085	.059	1.447 n.s.	.101	.054	1.882 +
Controls									
AI experience	.047	.049	.961 n.s.	.029	.070	.415 n.s.	.057	.082	.692 n.s.
Technology commitment	.025	.087	.291 n.s.	.073	.147	.494 n.s.	.004	.107	.034 n.s.
Negative attitude toward AI	(.104)	.042	(2.480) *	(.163)	.084	(1.947) n.s.	.053	.052	(1.026) n.s.
$\mathbf{R^2}$	.171			.197			.169		

Significance levels: $+ = p < .1$, $* = p < .05$, $** = p < .01$, $*** = p < .001$

Table 5.2: *Effects of Human- and AI-fit Appraisals on the Delegation Rate*

Next, we tested H2a and H2b, which hypothesized a moderation effect of AI knowledge on the relationship between human- and AI-fit appraisals and AI delegation behavior (i.e., more consistent AI delegation behavior). For a binary moderator (treatment group vs. control group), the literature advises estimating the effect for each group; then, one can test for a difference in the coefficients (Cohen et al., 2003; McCabe et al., 2018). Therefore, we ran two SEMs: one for the control group (Table 5.2, Model 2) and one for the treatment group (Table 5.2, Model 3). Adhering to established guidelines (Baron & Kenny, 1986; Clogg et al., 1995), we tested for a difference in the regression coefficients (slopes) using a Z-test. We find a significant difference between the two models in the coefficients of human-fit appraisal ($p < .05$) and AI-fit appraisal ($p < .05$). Therefore, we find support for H2a and H2b. Additionally, we observe that human-fit appraisal (negative) and AI-fit appraisal (positive) significantly affect delegation behavior only in the treatment group (Table 5.2, Model 2 vs. Model 3).

To enrich our understanding of the moderation effect, we further investigated the variables of AI delegation behavior, human-fit appraisal, and AI-fit appraisal. A by-group assessment shows that AI knowledge does not affect (two-sided t-test, $p > .1$) human-fit and AI-fit appraisals. However, AI knowledge significantly affects (two-sided t-test, $p < .01$) the delegation rate, leading to a 14.1pp increase (Table 5.3). No pattern in the control group's delegation rate was apparent, with the delegation rate almost equally spread across all delegation possibilities. In contrast, the treatment group's delegation rates shifted significantly toward the upper end of the spectrum (Figure 5.5). We conclude that altered AI delegation behavior mainly drives the moderation of AI knowledge (H2a & H2b). In other words, AI knowledge makes humans more consistent delegators by changing their behavior rather than their human-fit and AI-fit appraisals.

Group	**n**	**Delegation rate**			
		Min	Mean	Max	SD
Control	55	.000	.482	1.000	.339
AI Knowledge Treatment	56	.000	.623	1.000	.287

Table 5.3: *Descriptive Statistics of Delegation Rate*

Group	**n**	**Human-fit appraisal**				**AI-fit appraisal**			
		Min	Mean	Max	SD	Min	Mean	Max	SD
Control	55	2.750	5.500	7.000	.800	2.250	5.480	7.000	.971
AI Knowledge Treatment	56	1.750	5.348	6.625	.921	3.125	5.531	7.000	.921

Table 5.4: *Descriptive Statistics of Human- and AI-fit Appraisals*

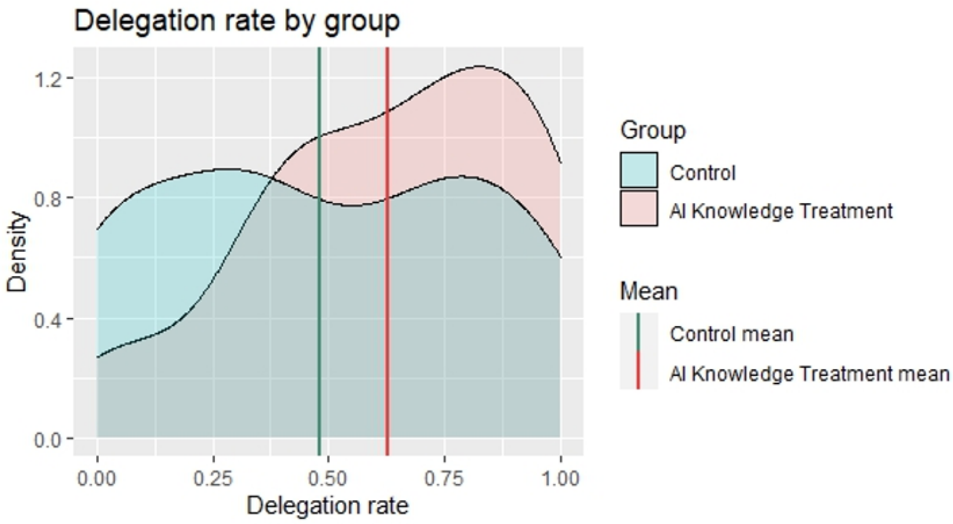

Figure 5.5: *Delegation Density by Group*

5.5.2 Effects on Performance and AI Usage Continuance Intention

H3a stated that increasing the delegation rate would have a positive impact on performance. We set up a linear regression model to test the hypothesis and find support for an increase in the delegation rate leading to a significantly better performance in image classification for the human-AI collaboration (Table 5.5, Model 4).

DV: Performance[A] / Variable	Model 4: Total dataset		
	Coef.	SE	t-value
Delegation rate	.208	.042	4.999***
$\mathbf{R^2}$	.184		

A = Classification Accuracy; Significance levels: $+ = p < .1$, $* = p < .05$, $** = p < .01$, $*** = p < .001$

Table 5.5: *Effect of the Delegation Rate on Performance*

Finally, we tested H3b, which stated that we expected AI knowledge to positively impact AUCI. To test H3b, we created a binary variable "group" representing the treatment condition (0 = control, 1 = treatment). We set up an SEM with the total dataset and tested the impact of the group variable on AUCI (Table 5.6, Model 5). This setup also allows for the inclusion of control variables. We find a significant effect of AI knowledge on AUCI. However, the effect is opposite to the initial hypothesis (H3b): The AI knowledge treatment decreased instead of increased AUCI. In summary, we must reject H3b but find support for an effect opposite to the hypothesized direction.

DV: AUCI Variable	Model 5: Total dataset Coef.	SE	t-value
Group (0 = control, 1 = AI knowledge treatment)	(.373)	.176	(2.117)*
Controls			
AI experience	(.074)	.159	(.467)
Technology commitment	.943	.280	3.374***
Negative attitude toward AI	(.121)	.128	(.950)
$\mathbf{R^2}$	.678		

Significance levels: $+ = p < .1$, $* = p < .05$, $** = p < .01$, $*** = p < .001$

Table 5.6: *Effect of AI Knowledge on AI Usage Continuance Intention (AUCI)*

5.6 Discussion

This paper investigated what determines AI delegation behavior and has shed light on the effects of AI knowledge in delegation-based human-AI collaboration. Our between-subjects experiment yielded three key findings. First, we find that task appraisal can explain AI delegation behavior for humans enabled with AI knowledge (key finding #1). Furthermore, we find that AI knowledge can improve human-AI collaboration performance by aligning AI delegation behavior more closely with task appraisal (key finding #2). Last, we also find that AI knowledge can reduce AUCI (key finding #3), which suggests that AI knowledge is not strictly positive for human-AI collaboration. Below, we discuss each finding's implications for HCI, the study's limitations, and future research directions.

5.6.1 Implications for Human-AI Collaboration Research and Practice

Key finding #1: Task appraisal can explain AI delegation behavior for humans enabled with AI knowledge. Prior research introduced the appraisal of a subordinate (AI) as one decisive factor of delegation behavior (Leana, 1987). We specify task appraisal in the AI context by distinguishing between its two driving forces: human-fit and AI-fit appraisals. We add that humans who delegate in human-AI collaborations appraise AI and human task fits. In other words, they also appraise their own attributes next to the AI's attributes. This finding supports prior research on AI delegation, which suggests that meta-knowledge (the knowledge of one's knowledge) is decisive in AI delegation (Fügener et al., 2021a). Understanding this mechanism is essential to understanding why humans delegate specific tasks and solve other tasks themselves.

Implications: The human appraisal of their attributes in AI delegation suggests new design implications for HCI research and practice. HCI research has produced several design guidelines and principles regarding AI in human-AI collaboration (Amershi et al., 2019; Vössing et al., 2022). However, the identified design principles primarily focus on AI and its attributes. Existing guidelines structure what an AI might communicate about itself in a human-AI collaboration, for example, "Make clear what the [AI] system can do" (Amershi et al., 2019) or how to behave in specific social situations, for example, "Match relevant social norms" (Amershi et al., 2019). The significance of human appraisal for AI delegation decisions indicates that we must consider human attributes in designing AI for human-AI collaboration. As a complement to the AI-attribute-focused principles above, a new design principle might state, "Make clear what humans can do." An AI could provide information on average (or even individualized) human performance to promote efficient delegation. On the other hand, AI might also state what humans cannot do. For example, it could make interacting humans aware of their biases ("Create awareness of human biases"). In practice, doctors could receive information on their classification accuracy (next to AI accuracy) and a reminder regarding human confirmation bias when making an image-based diagnosis. Overall, the finding extends the range of current AI design guidelines by suggesting human-attribute-focused design features to make AI more usable.

Key finding #2: AI knowledge can improve human-AI collaboration performance by aligning AI delegation behavior more closely with task appraisal. Prior studies identified the impact of different AI features on human-AI collaboration performance, for example, a positive effect from AI update compatibility (Bansal et al., n.d.). However, some features have mixed results, such as "explainable AI" features, which aim to make AI reasoning explicit (Arrieta et al., 2020; You et al., 2022). While the explained reasoning behind AI decisions can induce trust (Norkute et al., 2021), it can also confirm human biases and result in less thorough human reasoning, thus harming performance of a human-AI collaboration (Bansal et al., 2021; Bauer et al., 2023). Other research even asserts that there is a loss of unique human knowledge when interacting with AI (Fügener et al., 2021b). Our findings suggest considering the impact of "human features" (i.e., AI knowledge) on performance in delegation-based human-AI collaboration.

Implications: The performance-enhancing effect of AI knowledge translates into specific AI design implications. While explainable AI developments focus on explaining concrete AI decisions, our findings suggest including design features that convey a general understanding of AI. An "educational" (vs. "explainability") feature could equip humans with knowledge regarding AI's general functioning or its advantages and disadvantages. Such a feature would refrain from providing an easy-to-use heuristic, such as an explainability feature that potentially confirms human bias (Bansal et al., 2021; Bauer et al., 2023). Instead, it should enrich thorough human reasoning and work as a partner to enable reflection regarding one's own assessment. Of course, explainability will still play a significant role in AI research, especially given the increasing legal requirements. We are not arguing that explainable AI should be replaced, but rather that it should be complemented with AI knowledge dependent on the underlying context.

The findings show that humans with AI knowledge delegate a task if they appraise it as a good fit for an AI and do not delegate it if they appraise it as a good fit for humans, which seems intuitive. However, this implies that humans without AI knowledge exert partially illogical AI delegation behavior, as in our control group. Their delegation decisions are unaligned with their task appraisals. Hence, AI knowledge appears to be a prerequisite for consistent AI delegation behavior, which has implications beyond AI feature design. Besides including educational features in AI-based tools, practitioners must also invest in AI training and upskilling programs for humans that promote basic AI literacy, which might be difficult to learn while using an AI-based tool. The identified task appraisal (key finding #1) supports the conceptualization of AI knowledge into a technological and social part. Organizations can use this conceptualization to structure AI knowledge training programs for their employees. Most critically, such AI knowledge training should include knowledge of AI (technological part) and humans themselves (social part).

Key finding #3: AI knowledge can reduce AI usage continuance intention (AUCI). The user's intention to continue using AI is arguably one of the most critical metrics for HCI researchers and practitioners when designing AI for human-AI collaboration (Thong et al., 2006). A lack of human intention to use AI dooms human-AI collaboration from the outset. Prior studies have shown that, for example, AI competence perceptions (Hu et al., 2021) or parasocial relationships with AI (M. Lee & Park, 2022) drive human AI usage intention. Our findings suggest that AI knowledge can lower this critical metric of human-AI collaboration, suggesting a more refined view on the so far exclusively positively treated topic.

Implications: The immediate implication for HCI research and practice is that we must not implement AI knowledge features without assessing the underlying context. There is no one-size-fits-all approach to AI knowledge. AI designers must ask questions such as, "How relevant is AUCI in our context compared to other metrics like performance?" Furthermore, this finding implies the need to better understand the effects of AI knowledge. Prior research on information processing found that information overload in the technology context can invoke cognitive stress (Malhotra, 1982) or lower job satisfaction (Jacoby, 1984). Information overload might be a potential reason for lowered AUCI through AI knowledge and is worth exploring. HCI researchers need to better understand how to balance AI knowledge's positive and negative effects or which specific components of AI knowledge are decisive for the positive and negative effects of AI knowledge.

5.6.2 Limitations and Future Research

Our study has certain limitations that present interesting directions for future research. First, we used a non-specialized task and an acknowledged resource (i.e., ImageNet dataset) to ensure generalizability and consistency with prior research (Fügener et al., 2021a, 2021b). While we believe that the identified effects carry over into tasks such as social media content moderation, future research could investigate whether other effects exist in more specialized environments (e.g., medical contexts) or in different task settings (e.g., simple tasks). For example, medical doctors usually possess a high domain knowledge of image-based diagnoses (i.e., their medical training). Future research could investigate how the level of human domain knowledge (amateur vs. expert) influences the identified effects of AI knowledge. For simple tasks (e.g., when the presented answer options are distinct for humans), one should expect humans to never delegate to maximize performance (if AI occasionally errs and time is irrelevant). Future research might test whether AI knowledge-enabled humans will exhibit such expected rational behavior in simple task settings.

Second, our finding regarding lowered AUCI suggests that specific components of AI knowledge might have opposing effects on human attitudes or that an optimal knowledge level exists. On the one hand, future HCI research could pursue identifying the effects of more specific AI knowledge components (e.g., only social AI knowledge vs. only technological AI knowledge). It would be of great interest to specify these AI knowledge components for different stakeholder groups (e.g., for developers vs. managers). For example, future research could specifically identify the appropriate social and technological AI knowledge components for managers. On the other hand, HCI researchers could set out to find the level of AI knowledge that starts to harm performance or human attitudes (e.g., AUCI). For example, one could identify the specific depth of technological AI knowledge that helps managers and when it inhibits them in their decision-making.

Finally, due to its design, our experiment assessed only the short-term effects of AI knowledge enablement. It would be of great interest to test how persistent the AI knowledge enablement effects are over time (short-term vs. long-term). Furthermore, comparing different enablement methodologies (e.g., text-based learning vs. gamified learning) could provide valuable information regarding how to optimally convey AI knowledge. Such future studies could provide insightful details on designing educational AI features or planning AI upskilling programs.

5.7 Conclusion

This study proposed task appraisal as a decisive factor of AI delegation behavior and AI knowledge as a crucial moderator to facilitate efficient AI delegation. The results of our experimental study support how task appraisal determines AI delegation behavior for humans enabled by AI knowledge and show that AI knowledge aligns task appraisal with AI delegation behavior in a high-difficulty task setting, leading to higher performance. However, we also find that increasing AI knowledge reduces AUCI, which suggests a thorough, context-dependent evaluation should be undertaken before deployment. The findings imply also that AI knowledge should be considered when designing AI and that investing in human AI training and upskilling is highly relevant for organizations. We encourage the HCI community to engage in a more detailed investigation of AI knowledge to identify its beneficial and harmful effects, thus contributing to more productive human-AI collaboration in the future.

5.8 Appendix of Chapter 5

5.8.1 Appendix 5.A: Variable Measurement

Independent variable	**Item ID**	**Item (7-point Likert-type scale)**
Human-fit appraisal	HFA1	Humans are suited to solve this exercise.
AI-fit appraisal	AFA1	AI is suited to solve this exercise.

Table 5.7: *Measurement: Independent Variables*

Control variable	**Item ID**	**Item (7-point Likert-type scale)**
AI experience (AIX)	AIX1	AI was/is part of my formal education.
	AIX2	AI was/is part of my job.
	AIX3	I was part of more AI-related projects than the average person.
Technology commitment (TEC) (Neyer et al., 2016)	TEC1	I am very curious about new technical developments.
	TEC2	I am always interested in using the latest technical equipment.
	TEC3	Whether or not I am successful in using modern technology depends largely on me.
Negative attitude toward AI (NAA) (Nomura et al., 2006)	NAA1	I would feel uneasy if AI really had emotions.
	NAA2	Something bad might happen if AI developed into living beings.
	NAA3	I would feel uneasy if I was given a job where I had to use AI.

Table 5.8: *Measurement: Control Variables*

Dependent variable	**Item ID**	**Item (7-point Likert-type scale)**
AI usage continuance intention (AUCI) (Bhattacherjee, 2001; Thong et al., 2006)	AUCI1	I intend to continue using AI technology when it is offered to me.
	AUCI2	Using AI technology for future tasks is something I would do.
	AUCI3	I predict that I would use AI technology in the future when applicable.

Table 5.9: *Measurement: Dependent Variables*

Manipulation test variable	**Item ID**	**Item (7-point Likert-type scale)** I have a fair understanding of the...
Social AI knowledge manipulation	SAK1	...human strength “complex perception.”
	SAK2	...human strength “social intelligence.”
	SAK3	...human weakness “overconfidence bias.”
	SAK4	...human weakness “confirmation bias.”
Technological AI knowledge manipulation	TAK1	...AI strength “pattern recognition.”
	TAK2	...AI strength “learning capacity.”
	TAK3	...AI weakness “finite prediction class.”
	TAK4	...AI weakness “learning conditions.”

Table 5.10: *Measurement: Manipulation Test*

5.8.2 Appendix 5.B: Variable Validity

Variable	**Item ID**	**Loading**
AI experience (AIX)	AIX1	.93
	AIX2	.74
	AIX3	.85
Technology commitment (TEC)	TEC1	.69
	TEC2	.80
	TEC3	.64
Negative attitude toward AI (NAA)	NAA1	.63
	NAA2	.78
	NAA3	.85

Table 5.11: *Item Loadings*

	AIX	**TEC**	**NAA**	**Cronbach's Alpha**	**Composite Reliability**
AI experience (AIX)	.84			.87	.88
Technology commitment (TEC)	.80	.71		.75	.76
Negative attitude towardstoward AI (NAA)	.47	.54	.76	.81	.80

Table 5.12: *Correlation matrix for controlled constructs (square root of average variance extracted in bold)*

5.8.3 Appendix 5.C: Human Classification Performance

Image ID	**Average human performance** (Share of subjects that assigned the image to the correct image class)
1	.27
2	.15
3	.15
4	.21
5	.32
6	.38
7	.28
8	.46
Total average	.28

Table 5.13: *Average Human Performance Per Image*

6 Effects on Organizational Characteristics

Title:	AI Literacy for the Top Management: An Upper Echelons Perspective on Corporate AI Orientation and Implementation Ability
Authors:	Marc Pinski, Technische Universität Darmstadt, Germany Thomas Hofmann, Technische Universität Darmstadt, Germany Alexander Benlian, Technische Universität Darmstadt, Germany
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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 6,986 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 (IT Management), O30 (Innovation; Research and Development; Technological Change; Intellectual Property Rights), L22 (Firm Organization and Market Structure)

6.1 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; S. 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 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, 2022a). Also, initial IS research identified executives' lack of AI literacy as one crucial inhibiting factor to the development and adoption of AI in firms (J. 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 (J. 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 (J. 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 (M. 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 (J. 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 (M. 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 6,986 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 (F. Ding et al., 2014; J. 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; B. 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 (J. Li et al., 2021), and AI value realization, achieved through AI implementation (M. 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.

6.2 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 (Subsection 6.2.1). 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 (Subsection 6.2.2) and review the concepts of AI orientation and AI implementation ability (Subsection 6.2.3). An overview of the study's constructs, including a delineation of related constructs, is available in Table 6.1.

6.2.1 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, 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 (J. 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, 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 (F. 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 (J. 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 (J. 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, 2015; Scuik & Hess, 2022). Research and practice calling for greater AI literacy in all executive roles (Gordon, 2022; J. Yang et al., 2021) underscores that a perspective focused on the person rather than the role would provide additional insight.

6.2.2 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, Haas, & Franz, 2023; J. 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, Adam, & Benlian, 2023; B. 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 (The Joint ACM/AIS IS2020 Task Force et al., 2021). 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, 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- (B. 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 (J. Li et al., 2021; M. 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., 2020; 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.

6.2.3 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 (J. 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 (J. 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 (J. Li et al., 2021). AI orientation refers to a *"firm's overall strategic direction and goals associated with introducing and applying AI technology"* (J. Li et al., 2021) and thus guides AI-related strategic decisions, including AI-related investments and management practices (F. Ding et al., 2014; Y. 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 (J. 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 (M. Weber et al., 2022). Among the resources required to successfully implement AI, human resources have been identified as critical (Roepke et al., 2000; M. Weber et al., 2022). Gaining new talent necessary for AI implementation will require firms to establish policies governing HR-related processes (G. 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 (G. 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* (M. 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).

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.	J. 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 M. Weber et al. (2022)	Firm level
Firm type	A typical configuration of organizational resources that enables a 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, Adam, and Benlian (2023)	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.	J. 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

Table 6.1: *Overview of Used and Delineated Constructs*

6.3 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 (Figure 6.1). To address RQ1, we hypothesized two effects of TMT AI literacy on AI orientation (H1) and HR-related AI implementation ability (H2) (Subsection 6.3.1.1). In addition, we investigated the role of AI orientation in this interplay in greater detail (Subsection 6.3.1.2). 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 (Subsection 6.3.2). 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 Figure 6.1.

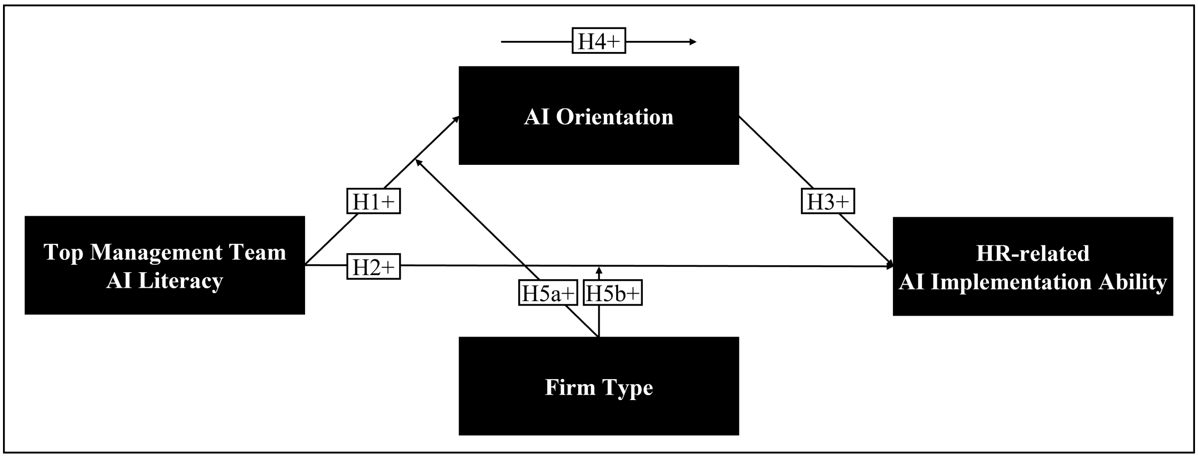

Figure 6.1: *Research Model*

6.3.1 Effects of TMT AI Literacy on AI Orientation and HR-related AI Implementation Ability

6.3.1.1 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 (J. 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 (J. Li et al., 2021).

How a strategic direction (e.g., AI orientation) is decided in the TMT also depends on the *power* of it 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 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:

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 (G. 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; M. 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., hire AI talent). As such, we hypothesize the following:

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

6.3.1.2 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 (Y. 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.

6.3.2 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 (M. 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 (M. 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 (J. 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").

6.4 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 (Subsection 6.4.1). After that, we describe the principal and control variables of the study and detail how we operationalized their measurement (Subsection 6.4.2). To ensure the validity of our analysis, we conducted several robustness checks, which are available in Appendix 6.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).

6.4.1 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).

6.4.1.1 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.

6.4.1.2 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 6.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 and 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.

6.4.2 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 6.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 (J. 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 6.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) (J. 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 6.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 6.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, 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 (J. 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 (κ = .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 (J. 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 (J. 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 6.3.

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 (F. Zhang et al., 2018).

6.5 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 (Subsection 6.5.1.1, Subsection 6.5.1.2, Subsection 6.5.2). Descriptive statistics and correlations are available in Table 6.2. A summary of the main results is available in Figure 6.2. The results of the conducted robustness checks are available in Appendix 6.B.

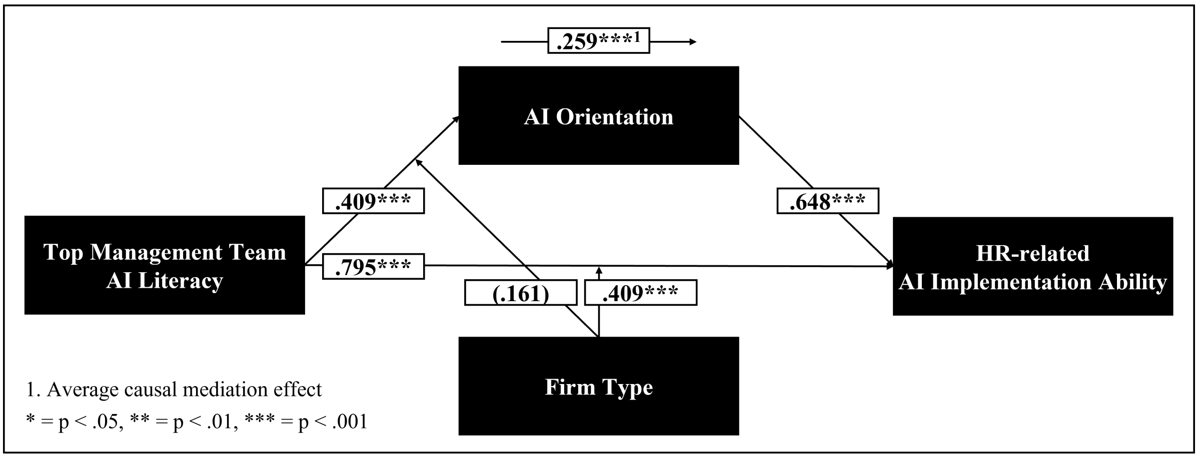

Figure 6.2: *Research Model with Results*

6.5.1 Effects of TMT AI Literacy on AI Orientation and HR-related AI Implementation Ability

6.5.1.1 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 6.3 and found that TMT AI literacy positively affects AI orientation ($\beta = .409, p < .001$). 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 6.3. 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 ($\beta = .795, p < .001$). Thus, we conclude support for H2.

Variable	Unit	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top management team AI literacy (1)	%	.084	.152	1							
AI orientation (2)	%	.031	.115	.503***	1						
HR-related AI implementation ability (3)	%	.108	.247	.662***	.555***	1					
Firm type (4)	Binary (0 = incumbent, 1 = startup)	.260	.439	.574***	.208***	.389***	1				
CIO presence (5)	%	.282	.450	(.175)***	(.113)**	(.157)***	(.309)***	1			
CTO presence (6)	%	.389	.488	.243***	.082*	.122**	.316***	(.147)***	1		
TMT size (7)	# Executives	10.7	4.7	(.062)	(.002)	(.023)	(.123)**	.281***	.154***	1	
Firm age (8)	Years	56.2	60.4	(.312)***	(.128)**	(.232)***	(.483)***	.243***	(.178)***	.135***	1
Firm size (9)	# Employees	42717	130473	(.066)	.014	(.055)	(.190)***	.040	(.007)	.088*	.094*
Number of job postings (10)	# Job postings	307	350	(.220)***	(.026)	(.156)***	(.426)***	.176***	(.107)**	.092*	.253***
IT orientation (11)	%	.019	.084	.039	(.020)	.026	.006	(.037)	.033	(.001)	.020

Variable	Unit	(9)	(10)	(11)
Top management team AI literacy (1)	%			
AI orientation (2)	%			
HR-related AI implementation ability (3)	%			
Firm type (4)	Binary (0 = incumbent, 1 = startup)			
CIO presence (5)	%			
CTO presence (6)	%			
TMT size (7)	# Executives			
Firm age (8)	Years			
Firm size (9)	# Employees	1		
Number of job postings (10)	# Job postings	.355***	1	
IT orientation (11)	%	(.014)	(.003)	1

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

Table 6.2: *Descriptive Statistics and Correlations (n = 645)*

DV (Model ID)	AIO[1] (1)		HAIIA[2] (2)		HAIIA (3)		AIO (4)		AIO (5)		HAIIA (6)		HAIIA (7)	
Variable	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*
Constant	(.021)	.042	.009	.073	.057	.083	(.017)	.042	(.015)	.042	.006	.073	.002	.073
TMT AI literacy (TMTAIL)	**.409*****	**.029**	**.795*****	**.59**			**.426*****	**.032**	**.559*****	**.077**	**.783*****	**.064**	**.439****	**.140**
Mediator														
AI orientation (AIO)			**.648*****	**.070**	**1.107*****	**.070**					**.649*****	**.070**	**.664*****	**.070**
Moderator														
Firm type (FT)							**(.018)**	**.015**	**(.005)**	**.016**	**.012**	**.026**	**(.020)**	**.029**
TMTAIL × FT									**(.161)**	**.084**			**.409*****	**.148**
Controls														
CIO presence	(.016)	.010	(.015)	.017	(.017)	.019	(.018)	.010	(.018)	.010	(.014)	.017	(.013)	.017
CTO presence	(.010)	.009	(.024)	.015	.005	.017	(.009)	.009	(.011)	.009	(.025)	.016	(.019)	.016
TMT size	.001	.001	.001	.002	<.001	.002	.001	.001	.001	.001	.001	.002	.002	.002
Firm age	<.001	<.001	<.001	<.001	<.001*	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Firm size	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Number of job postings	<.001	<.001	<.001	<.001	<.001*	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
IT orientation	(.060)	.047	.028	.082	.079	.093	(.062)	.047	(.068)	.047	.030	.082	.048	.082
Industry controls														
Agriculture[3]	(.003)	.064	<.001	.113	.006	.128	(.006)	.064	(.012)	.064	.002	.113	.017	.112
Construction	.005	.057	(.016)	.101	(.006)	.114	.004	.057	<.001	.057	(.016)	.101	(.005)	.100
Finance and insurance	(.006)	.042	(.011)	.074	.027	.084	(.002)	.043	(.007)	.043	(.013)	.075	(.002)	.074
Health care[4]	(.008)	.045	.018	.079	.062	.090	.001	.046	(.007)	.046	.012	.080	.030	.080
Information	(.001)	.056	(.013)	.097	(.015)	.111	(.003)	.056	(.005)	.056	(.011)	.098	(.006)	.097
Manufacturing	.017	.041	.026	.073	.050	.082	.017	.041	.012	.041	.026	.073	.037	.072
Mining[5]	.014	.046	(.009)	.081	.005	.092	.014	.046	.010	.046	(.009)	.081	.001	.081
PST service[6]	.008	.042	.028	.074	.107	.083	.013	.042	.007	.042	.024	.074	.039	.074
Real estate[7]	.013	.045	(.004)	.079	(.019)	.090	.011	.045	.009	.045	(.002)	.079	.002	.079
Retail trade	<.001	.046	(.015)	.080	.014	.090	.003	.046	.002	.046	(.017)	.080	(.013)	.079
Transportation[8]	(.022)	.045	.106	.078	.167	.088	(.016)	.045	(.022)	.045	.101	.079	.117	.078
Utilities	.013	.050	.026	.088	.006	.099	.011	.050	.010	.050	.028	.088	.030	.087
Wholesale trade	.056	.050	(.019)	.087	(.033)	.099	.056	.050	.055	.050	(.020)	.088	(.018)	.087
R^2	.279		.521		.381		.281		.285		.521		.527	
Adjusted R^2	.255		.504		.360		.256		.259		.503		.508	
P-value of f-statistic	<.001		<.001		<.001		<.001		<.001		<.001		<.001	
n	645		645		645		645		645		645		645	

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

Table 6.3: *Regression Results*

6.5.1.2 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 6.3. 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 ($\beta = .648, p < .001$). 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 × b represents the "average causal mediation effect" while path c represents the "average direct effect." The collected data were resampled 5,000 times as part of the bootstrapping process, following previous IS research (N. P. 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 6.4summarizes the results of our mediation analysis. Both paths ($a \times b[\beta = .259]$ and $c[\beta = .816]$) are significant. The proportion of the total effect on HR-related AI implementation ability mediated by AI orientation is .241. Hence, we conclude support for H4.

6.5.2 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

Effects	**Estimate (β)**	**95%-Confidence Interval**		**Zero**
		Lower bound	Upper bound	**included**
Average causal mediation effect (ACME = Path a × b)	.259*	.166	.370	No
Average direct effect (ADE = Path c)	.816*	.651	.970	No
Total effect (TE = ACME + ADE)	1.075*	.936	1.220	No
Proportion mediated (= AMCE / TE)	.241*	.155	.350	No

Table 6.4: *AI Orientation's Mediation Effect of TMT AI Literacy's Effect on AI Implementation Ability*

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 affects AI orientation (Table 6.3, model 4) or HR-related AI implementation ability (Table 6.3, model 6). Therefore, 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 ($\beta = (.018), p > .05$) nor HR-related AI implementation ability ($\beta = (.012), p > .05$). 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 ($TMTAIL \times FT : \beta = (.161), p > .05$). 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 ($TMTAIL \times FT : \beta = .409, p < .01$). 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 6.3 (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.

6.6 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

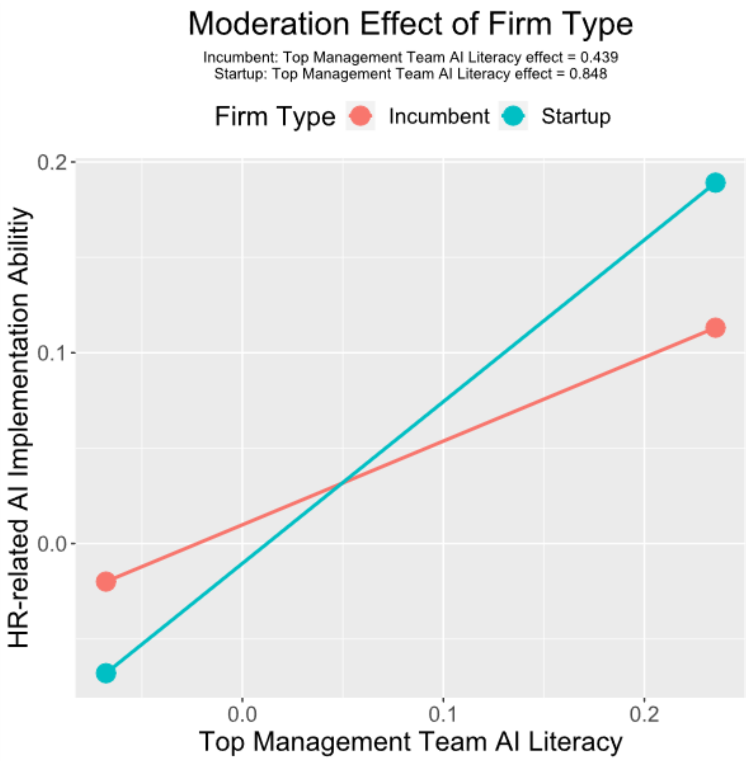

Figure 6.3: *Moderation Effect of Firm Type on the Relationship between TMT AI Literacy and HR-related AI Implementation Ability*

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 (J. 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 and Gupta, 2021; M. 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 (J. 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., D. Q. 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; C. 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 and Gupta, 2021; Pumplun et al., 2019; M. 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, 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 (J. 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 (G. 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.

6.6.1 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., J. Li et al., 2021) or AI implementation (e.g., Mikalef and Gupta, 2021; M. 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.

6.6.2 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).

6.6.3 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 6.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 (M. 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.

6.7 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.

6.8 Appendix of Chapter 6

6.8.1 Appendix 6.A: List of AI Skills and Competencies

AI skills and competencies	
AI ChatBot	MLPACK
AI KIBIT	Mlpy
ANTLR	Modular Audio Recognition Framework
Apertium	MoSes
Artificial Intelligence	MXNet
Automatic Speech Recognition	Natural Language Processing
Caffe Deep Learning Framework	Natural Language Toolkit
Chatbot	ND4J
Computational Linguistics	Nearest Neighbor Algorithm
Computer Vision	Neural Networks
Decision Trees	Object Recognition
Deep Learning	Object Tracking
Deeplearning4j	OpenCV
Distinguo	OpenNLP
Google Cloud Machine Learning Platform	Pattern Recognition
Gradient boosting	Pybrain
H2O	Random Forests
IBM Watson	Recommender Systems
Image Processing	Semantic Driven Subtractive Clustering Method
Image Recognition	Semi-Supervised Learning
IPSoft Amelia	Sentiment Analysis
Ithink	Sentiment Classification
Keras	Speech Recognition
Latent Dirichlet Allocation	Supervised Learning
Latent Semantic Analysis	Support Vector Machines
Lexalytics	TensorFlow
Lexical Acquisition	Text Mining
Lexical Semantics	Text to Speech
Libsvm	Tokenization
Machine Learning	Torch
Machine Translation	Unsupervised Learning
Machine Vision	Virtual Agents
Madlib	Vowpal
Mahout	Wabbit
Microsoft Cognitive Toolkit	Word2Vec
	Xgboost

Table 6.5: *List of AI Skills and Competencies*

6.8.2 Appendix 6.B: Robustness Checks

We ran several robustness checks to ensure the validity of our findings: AI distinctiveness of principal variables (6.B.1), alternative operationalization of principal variables (6.B.2), sample selection bias (6.B.3), analyses segmented by firm type (6.B.4), and reverse causality regarding AI orientation (6.B.5). Additional checks were made as stated below, and Tables 6.6 and 6.8 summarize the robustness findings.

6.8.2.1 Appendix 6.B.1: Distinctiveness of AI Orientation and HR-related AI Implementation Ability

We tested whether AI orientation and HR-related AI implementation ability are distinct from their general IT counterparts (IT orientation and HR-related IT implementation ability). Prior IS research found that TMTs usually do not discuss general IT-related matters in greater detail (Huff et al., 2008). Whereas TMTs seem to normally trust general IT and perceive it as less of a risk, they consider AI from a different perspective (J. Li et al., 2021). Hence, we argue that the orientation of a firm towards AI or IT and the subsequently demanded HR-related implementation ability are qualitatively distinct.

To test that AI orientation and HR-related AI implementation ability are distinct, we used two regression models where we replaced them as dependent variables with their general IT counterparts. We find that TMT AI literacy is neither associated with IT orientation (Table 6.6, Model 8: $\beta = .015, p > .05$) nor HR-related IT implementation ability (Table 6.6, Model 9: $\beta = (.050), p > .05$). Additionally, one can observe that IT orientation is uncorrelated with AI orientation and HR-related AI implementation ability (Table 6.2). In summary, we conclude that the robustness of our analysis is supported by the distinctiveness of AI (vs. general IT).

6.8.2.2 Appendix 6.B.2: Alternative Operationalization of AI Orientation and HR-related AI Implementation Ability

Our main analysis argues that the frequency of AI terms within a firm's strategic communication indicates the degree of its AI orientation. Thus, we operationalize AI orientation as a continuous variable. While we account for industry effects with control variables, one could argue that even within a specific industry, multiple business models exist that differ in their applicability of AI (Dellermann et al., 2018). While a strong strategic direction toward AI might be most purposeful for some, others can use AI only in specific niche cases. To increase the robustness of our analysis, we construct a binary

AI orientation variable (see subsection 5.4.2). The binary variable measures whether AI is discussed in a firm's strategy at all and not how much it is discussed. Hence, it accounts for further differences in business models within a given industry. We find that TMT AI literacy also significantly affects binary AI orientation (Table 6.6, Model 10: $\beta = 1.053, p < .001$).

Based on the same logic, one could also argue that a firm's share of AI skills within its workforce depends on the business model. More AI skills might not necessarily be better (see subsection 5.4.2). We constructed a binary variable of HR-related AI implementation ability (HAIIA-binary), measuring whether a firm considers AI skills at all. In model 11 (Table 6.6), we find that both TMT AI literacy ($\beta = .349, p < .05$) and AI orientation ($\beta = .390, p < .05$) significantly affect this alternative operationalization of HAIIA-binary, as in our original model 2. Furthermore, one could argue that not only the share of AI skills in the workforce matters but also the AI skill breadth (see subsection 5.4.2). In model 12 (Table 6.6), we tested how TMT AI literacy ($\beta = 1.212, p < .001$) and AI orientation ($\beta = 1.826, p < .001$) affect "HAIIA-breadth." Both coefficients are significant and in the same direction as in our original model 2. In summary, we conclude that the alternative operationalizations of AI orientation and HR-related AI implementation ability support the robustness of our analysis.

6.8.2.3 Appendix 6.B.3: Sample Selection Bias

We used the world's largest professional social network (LinkedIn.com) for data collection to ensure that we included a firm's breadth of job postings as comprehensively as possible, ultimately describing its HR-related AI implementation ability. However, using only one source of job postings could lead to sample selection bias since firms might post their open positions with a different focus on different platforms. Therefore, we additionally collected the firms' job postings from Indeed.com, another sizeable online job market (> 250 million unique visitors per month, Indeed.com, 2023). Of the 645 firms in our data set, 605 also advertised job postings on Indeed.com. We collected and processed the firm's job postings from Indeed.com with the same approach used for LinkedIn.com. In model 13 (Table 6.6), we ran model 2 (dependent variable: HR-related AI implementation ability) with an alternative dependent variable based on the data retrieved via Indeed.com instead of LinkedIn.com (dependent variable: HAIIA-Indeed). We found that the effects of TMT AI literacy and AI orientation on HAIIA-Indeed are also significant. Therefore, we conclude that the robustness check reduces concerns that our sample retrieved via Linked.com suffers from sample selection bias.

6.8.2.4 Appendix 6.B.4: Analysis by Firm Type

While public firms (like our sample of incumbent firms) must disclose specific financial data, private firms (like our sample of startup firms) are not subject to such obligations. To further support the robustness of our analysis, we conducted analyses segmented by firm type, allowing us to control for the relevant financial data within the subsample of incumbent firms (J. Li et al., 2021). In models 14-16 (Table 6.7), we replicated the main models 1-3 only for incumbent firms, including the introduced financial variables. In models 17-19 (Table 6.7), we replicated the main models 1-3 only for startup firms. In both segmentations (models 14-16 and 17-19), the significant effects of the principal variables identified in models 1-3 hold (i.e., between TMT AI literacy, AI orientation, and HR-related AI implementation ability). We conclude that replicating the main effects in a "firm-type segmentation" supports the robustness of our main analysis. Furthermore, the analysis for incumbent firms only shows that the effects hold, even when including the financial control variables ownership concentration, net income, cost of goods sold, overhead costs, and leverage (Table 6.7, models 14-16). Descriptive statistics and correlations of the incumbent firm segment analysis, including financial control variables, are available in Appendix 6.D (Table 6.8).

6.8.2.5 Appendix 6.B.5: Reverse Causality Regarding AI Orientation

Prior research has shown that CIO presence affects AI orientation and has provided corresponding robustness checks regarding reverse causality (J. Li et al., 2021). Thus, our analysis assumes that TMT AI literacy as a character trait of executives on a firm's TMT also predicts AI orientation. However, one could argue that a firm with a higher AI orientation attracts AI-literate executives. To support our causal ordering and to diminish concerns regarding reverse causality of AI-literate executives and AI orientation, we also collected data on the incumbent firms' AI orientation from an earlier point in time, extending our data set to a panel. We follow J. Li et al. (2021) to construct our panel. Therefore, we obtained the 10-k statements, which include the MD&As (and thus also AI orientation) of each incumbent firm three years before their 2022 10-k statement using the same methodology. Furthermore, we collected each executive's tenure, which is available in their online profile (the average tenure of an executive was 4.97 years). Subsequently, we tested for a significant difference in the share of AI-literate executives who newly joined a firm's TMT within the last three years for firms that increased their AI orientation compared to firms that did not increase their AI orientation during the period. We found no significant difference in the share of AI-literate executives who joined the TMTs of firms with increased AI orientation compared to firms without increased AI orientation (two-sided t-test: $p > .05$). Thus, we conclude that the robustness check diminishes concerns that AI orientation affects TMT AI literacy rather than TMT AI literacy affecting AI orientation.

6.8.3 Appendix 6.C: Results of Robustness Checks

DV (Model ID)	**IIO**[1] (8)		**HITIA**[2] (9)		**AIO-binary**[3] (10)		**HAIIA-binary**[4] (11)		**HAIIA-breadth**[5] (12)		**HAIIA-Indeed** (13)	
Variable	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*
Constant	.032	.036	(.005)	.041	.008	.157	.033	.174	.035	.129	.001	.002
TMT AI literacy (TMTAIL)	**.015**	**.025**	(**.050**)	**.029**	**1.053*****	**.110**	**.349***	**.141**	**1.212*****	**.104**	**.021*****	.002
Mediator												
AI orientation (AIO)							**.390***	**.167**	**1.826*****	**.124**	**.030*****	**.002**
Controls												
CIO presence	(.007)	.008	.007	.009	(.052)	.036	(.033)	.040	(.004)	.030	<.001	.001
CTO presence	.004	.007	(.005)	.009	.062	.033	.051	.037	(.029)	.027	(.001)	<.001
TMT size	<.001	.001	.001	.001	.002	.003	.005	.004	<.001	.003	<.001	<.001
Firm age	<.001	<.001	<.001	<.001	(.001**)	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Firm size	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Number of job postings	<.001	<.001	<.001	<.001	<.001	<.001	.001***	<.001	<.001	<.001	<.001	<.001
IT orientation			.307***	.046	.097	.175	(.116)	.196	.141	.145	.001	.002
Industry controls												
Agriculture[6]	(.037)	.055	.020	.063	(.038)	.241	.585*	.268	(.017)	.199	(.001)	.003
Construction	(.035)	.049	.093	.056	.167	.215	.435	.240	(.037)	.177	(.001)	.003
Finance and insurance	(.030)	.036	.022	.042	.160	.159	.461**	.177	(.029)	.131	(.001)	.002
Health care[7]	(.012)	.039	.062	.044	.293	.169	.441*	.188	(.024)	.139	<.001	.002
Information	(.033)	.048	.006	.055	(.074)	.209	.140	.232	(.018)	.172	<.001	.003
Manufacturing	(.013)	.035	.059	.041	.131	.155	.472**	.173	.028	.128	<.001	.002
Mining[8]	(.034)	.039	.060	.045	.094	.173	.245	.193	(.033)	.143	<.001	.002
PST service[9]	(.011)	.036	.038	.041	.309	.158	.345*	.176	.038	.130	.001	.002
Real estate[10]	(.021)	.039	.113*	.044	(.002)	.170	.142	.189	(.014)	.140	<.001	.002
Retail trade	(.010)	.039	.006	.045	.066	.171	.213	.190	(.027)	.141	<.001	.002
Transportation[11]	(.021)	.038	.040	.044	.293	.167	.490**	.186	.085	.137	.003	.002
Utilities	(.034)	.043	.030	.049	.013	.188	.518*	.209	.027	.154	<.001	.003
Wholesale trade	(.028)	.043	.063	.049	.240	.187	.352	.209	(.070)	.154	(.001)	.003
R^2	.014		.127		.325		.218		.576		.544	
Adjusted R^2	(.017)		.097		.303		.190		.561		.527	
P-value of f-statistic	.981		<.001		<.001		<.001		<.001		<.001	
n	645		645		645		645		645		605	

Notes: 1. IT Orientation; 2. IT-related AI implementation ability; 3. AI orientation binary; 4. HR-related AI implementation ability binary; 5. HR-related AI implementation ability breadth; 6. Agriculture, forestry, fishing, and hunting; 7. Health care and social assistance; 8. Mining, quarrying, and oil and gas extraction; 9. Professional, scientific, and technical services; 10. Real estate and rental and leasing; 11. Transportation and warehousing; Significance levels: * = p < .05, ** = p < .01, *** = p < .001

Table 6.6: *Results of Robustness Checks (1/2)*

DV (Model ID)	AIO[1] (14)		HAIIA[2] (15)		HAIIA (16)		AIO (17)		HAIIA (18)		HAIIA (19)	
Variable	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*	β	*s.e.*
Constant	<.001	.035	.028	.050	.027	.052	(.073)	.063	(.233*)	.116	(.029)	.129
TMT AI literacy (TMTAIL)	**.573*****	**.058**	**.438*****	**.093**			**.393*****	**.057**	**.850*****	**.121**		
Mediator												
AI orientation (AIO)			**.556*****	**.069**	**.693*****	**.064**			**.696*****	**.148**	**1.199*****	**.149**
Controls												
CIO presence	(.016*)	.007	(.004)	.011	<.001	.011	(.037)	.057	(.037)	.106	(.005)	.122
CTO presence	(.008)	.008	.004	.011	.012	.012	(.016)	.028	(.110*)	.051	(.086)	.058
TMT size	.001	.001	.001	.001	.001	.001	.005	.005	.016	.008	.011	.010
Firm age	<.001	<.001	<.001	<.001	(.001**)	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Firm size	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Number of job postings	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
IT Orientation	(.038)	.041	.202***	.059	.229***	.060	(.162)	.139	(.403)	.258	(.311)	.295
Financial controls												
Ownership concentration	.011	.128	(.118)	.187	(.126)	.191						
Net income	<.001	<.001	<.001	<.001	.000*	<.001						
Cost of goods sold	<.001	<.001	<.001	<.001	<.001	<.001						
Overhead costs	<.001	<.001	<.001	<.001	<.001	<.001						
Leverage	(.015)	.014	(.005)	.020	(.007)	.021						
Industry controls												
Agriculture[3]	(.019)	.048	.013	.069	.030	.071						
Construction	(.006)	.043	(.003)	.062	.008	.063						
Finance and insurance	(.007)	.032	.022	.047	.033	.048						
Health care[4]	(.005)	.044	(.022)	.064	(.013)	.065	.013	.047	.094	.087	.072	.100
Information	(.014)	.042	(.017)	.060	(.011)	.062						
Manufacturing	.006	.031	.029	.045	.038	.046	.036	.057	.174	.106	.291*	.120
Mining[5]	.004	.034	.005	.050	.014	.051						
PST service[6]	(.018)	.032	.028	.047	.047	.048	.044	.038	.099	.071	.142	.081
Real estate[7]	.002	.035	(.001)	.050	.002	.052						
Retail trade	(.002)	.034	(.017)	.049	(.012)	.050						
Transportation[8]	(.014)	.037	.053	.054	.066	.055	(.003)	.049	.186*	.091	.213*	.104
Utilities	.006	.038	.026	.055	.026	.056						
Wholesale trade	.053	.038	(.008)	.055	(.010)	.057						
R^2	.229		.331		.298		.285		.521		.368	
Adjusted R^2	.184		.291		.258		.230		.481		.319	
P-value of f-statistic	<.001		<.001		<.001		<.001		<.001		<.001	
n	477		477		477		168		168		168	

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

Table 6.7: *Results of Robustness Checks (2/2)*

6.8.4 Appendix 6.D: Descriptive Statistics and Correlations

Variable	Unit	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top management team AI Literacy (1)	%	.032	.063	1							
AI orientation (2)	%	.017	.080	.432***	1						
HR-related AI implementation ability (3)	%	.051	.125	.428***	.467***	1					
CIO presence (4)	%	.365	.482	.015	(.071)	(.059)	1				
CTO presence (5)	%	.298	.458	.202***	.049	.107*	(.093)*	1			
TMT size (6)	# Executives	11.0	5.1	.108*	.048	.063	.268***	.179***	1		
Firm age (7)	Years	73.5	61.5	(.111)*	(.051)	(.117)*	.116*	(.038)	.092*	1	
Firm size (8)	# Employees	57409	148997	.125**	.092*	.045	(.021)	.066	.07	.003	1
Number of job postings (9)	# Job postings	396	364	.12**	.135**	.042	.051	.032	.043	.06	.312***
IT orientation (10)	%	.019	.084	.102*	.006	.165***	(.039)	.056	(.018)	.031	(.015)
Ownership concentration (11)	%	.103	.030	(.096)*	(.066)	(.093)*	.05	(.133)*	(.063)	(.04)	(.217)***
Net income (12)	k USD	3357.9	7549	.191***	.117*	.148**	(.046)	.085	(.043)	.041	.309***
Cost of goods sold (13)	k USD	16379.2	39188	.059	.076	.008	(.008)	.019	(.019)	.014	.67***
Overhead costs (14)	k USD	5180.47	10733	.085	.093*	.051	(.016)	.073	(.014)	.085	.822***
Leverage (15)	%	.671	.263	(.064)	(.045)	(.076)	.049	.034	.113*	.101*	.068

Variable	Unit	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Top management team AI Literacy (1)	%							
AI orientation (2)	%							
HR-related AI implementation ability (3)	%							
CIO presence (4)	%							
CTO presence (5)	%							
TMT size (6)	# Executives							
Firm age (7)	Years							
Firm size (8)	# Employees							
Number of job postings (9)	# Job postings	1						
IT orientation (10)	%	0	1					
Ownership concentration (11)	%	(.203)***	(.014)	1				
Net income (12)	k USD	.21***	(.05)	(.196)***	1			
Cost of goods sold (13)	k USD	.21***	(.05)	(.196)***		1		
Overhead costs (14)	k USD	.369***	(.013)	(.251)***	.553***	.614***	1	
Leverage (15)	%	.184***	(.039)	(.022)	.022	.067	.106*	1

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

Table 6.8: *Descriptive Statistics and Correlations for Incumbent Firms Only (including financial control variables, n = 477)*

7 Overarching Contributions and Conclusion

In recent years, AI technologies have made astonishing leaps concerning what they are capable of, leading to the increasing permeation of society and businesses with technology based on AI, as well as significant academic attention on the topic (Berente et al., 2021; M. Weber et al., 2022). However, these capability leaps are inseparably bundled with new facets of the technology that challenge our understanding of how technology functions and how we interact and collaborate with it (Schuetz & Venkatesh, 2020). As such, our understanding of what constitutes human literacy concerning this new type of technology and how it affects us and our organizations are changing. This dissertation is motivated by the potential that AI literacy, as a new type of human literacy, can have for individuals in their daily interactions and collaborations with AI, as well as for human organizations, that are often the decisive entities for the adoption of a particular technology. The presumption that human enablement, such as AI literacy, is beneficial for individuals and organizations generally seems sensible, based on what we know about prior human enablement, such as digital literacy (Eshet-Alkalai, 2004). However, since AI has broken fundamental assumptions about technology, many questions concerning the substance and implications of AI literacy remain unanswered. Against this backdrop, this dissertation asked three overarching research questions focusing on the (1) conceptualization, measurement, and enablement of AI literacy as well as (2) the effects of AI literacy on individuals and (3) on organizations.

To answer these research questions, my co-authors and I conducted five studies, which have been published in academic journals and conference proceedings. The first three articles are concerned with the exploration of the construct of AI literacy, addressing the first research question. Moreover, the third article, together with the fourth article, addresses the second research question, shedding light on the effects of AI literacy on AI-related human cognition and behavior. The fifth article addresses the third research question, taking an organizational perspective on AI literacy.

The results of the first three articles show that AI literacy is a distinct and relevant yet multifaceted and complex construct. By conceptualizing AI literacy and operationalizing it for measurement and enablement, the studies address the challenge of making AI literacy tangible and enabling its empirical exploration. Drawing on this foundation, the results of studies three and four show that AI literacy can enable humans to make more appropriate delegation decisions in a human-AI collaboration context and positively influence one's attitude towards AI. However, the results also present mixed findings concerning the relationship between AI literacy and human intentions to continue using AI, indicating the need to consider further factors in the future. The fifth study finds that the AI literacy of TMTs has effects not only on the strategic AI orientation of their organization but also on the ability to implement AI. Therefore, AI literacy is also a key enabler for the adoption of AI solutions in organizations.

As such, the findings of these five articles address the three overarching research questions. Combined, they contribute to theory and research and have valuable implications for practice that are covered in further detail below (Subsections 7.1 and 7.2). Moreover, this chapter discusses the limitations and most promising opportunities for future research (Subsection 7.3) before concluding the thesis overall (Subsection 7.4).

7.1 Contributions to Research and Theory

The overarching contributions of this dissertation to research and theory are threefold. By answering each of the three research questions, the thesis contributes to different aspects of the AI literacy discourse. More precisely, the thesis establishes a comprehensive and specific understanding as well as a usable operationalization of the construct of AI literacy (Subsection 7.1.1, answering RQ1), provides a nuanced view of the effects of AI literacy on humans (Subsection 7.1.2, answering RQ2), and bridges AI literacy research and research on organizational characteristics (Subsection 7.1.3, answering RQ3).

7.1.1 Contributions to Research on AI Literacy Conceptualization and Operationalization

Prior literature aiming to establish AI literacy as a construct identified a variety of relevant aspects (e.g., Cetindamar et al., 2022; Long and Magerko, 2020). However, many studies have not defined the term AI before building their AI literacy research on it. Since AI literacy builds on the prior technology literacy discourse (e.g., Eshet-Alkalai, 2004; Wolff et al., 2016) but at the same also challenges fundamental assumptions of technology (Schuetz & Venkatesh, 2020), it is paramount to work towards an understanding that comprehensively covers all new literacy aspects and makes it explicit which existing aspects have (not) changed. The first article of this thesis contributes to such an understanding by explicitly following an established definition that proposes three AI facets (autonomy, learning, and inscrutability) when conceptualizing AI literacy (Berente et al., 2021). By analyzing which components of AI literacy are specific to AI and which have shifted in relevance compared to prior technology literacy, the article contributes to a comprehensive and specific conceptualization. Furthermore, the existing literature has focused on individual groups of AI users, like medical doctors (Charow et al., 2021) or teachers (Kim & Kwon, 2023). Research also acknowledges that beyond a certain basic general level, AI literacy is stakeholder-specific (Arrieta et al., 2020). However, many relevant AI user groups (e.g., policymakers) have not been identified and explored until now. The first article also contributes a comparative examination of various AI user groups, changing the conversation to be more attentive to the needs of individual user groups, including those omitted until now.

Next to a conceptual understanding of a new phenomenon, useful operationalizations are crucial for its investigation. Prior research developed specialized measurement instruments, such as measurement instruments for competencies to interact with smart speakers (Wienrich & Carolus, 2021) or for the usage of AI only (B. Wang et al., 2022), neglecting other forms of interactions with or management of AI technology. While specialized measurement instruments are highly useful in their respective context, a more general measurement instrument targeted at the basic AI literacy everyone needs is also relevant for future research. The second article of this dissertation contributes such a measurement instrument. It is geared towards general AI literacy and provides researchers with a versatile tool to reliably measure a general form of AI literacy relevant to many (non-expert) stakeholders, such as non-technical employees in organizations that engage with AI.

Moreover, empirical research often requires not only measuring a construct but also manipulating it to uncover specific aspects. With regards to AI literacy, manipulation refers to enabling humans with such literacy. Prior research developed various learning experiences to enable students with AI literacy (e.g., Kandlhofer et al., 2016; Ng et al., 2022). However, most of these studies are focused on formal learning experiences (e.g., I. Lee et al., 2021) or children (e.g., Long et al., 2022). The third article of this thesis extends the discourse on AI literacy enablement to non-expert adults. While this group has so far been mostly neglected concerning AI literacy, it is highly relevant for non-expert adults to obtain AI literacy to keep up with the evolving skill requirements in the labor market (Alekseeva et al., 2021). Specifically, the third article generates design knowledge in the form of theory-driven and empirically evaluated design principles for informal AI literacy learning experiences targeted at non-expert adults. This design knowledge contributes to the toolbox that researchers can draw on to reliably enable (i.e., manipulate) AI literacy for further investigations.

7.1.2 Contributions to Research on AI Literacy Effects on Individuals and Cognitive Appraisal Theory

There is limited prior research on the effects of AI literacy on individuals. Studies assessing the consequences of AI literacy for humans, for example, identified positive influences on individuals' critical assessment abilities of AI (Druga & Ko, 2021) or the abilities to discern biases (Melsión et al., 2021). However, to continue improving human-AI interactions and collaborations, it is necessary to understand how further relevant aspects of human cognition and behavior are affected by AI literacy. For example, human intentions and attitudes concerning AI might have a significant impact on the success of human-AI collaborations (P. Zhang, 2013). The third and fourth articles of this thesis extend the literature on the effects of AI literacy on individuals with a nuanced view on delegation behavior as well as attitude towards AI and intention to continue using AI. While AI literacy aligns delegation behavior with task fit assessments and positively influences attitude towards AI, the articles present a mixed picture concerning AI literacy's effect on intentions to continue using AI, indicating that other context factors might affect the directionality of the effect. As such, this thesis presents a new perspective on AI literacy, which has been viewed as unilaterally positive by most prior studies (Casal-Otero et al., 2023). This is not to say that AI literacy should not be developed, but rather that a careful assessment of the context and the specific form of AI literacy is advisable for different situations. For example, overly technical AI terms and knowledge might reduce usage intentions for some, while those terms might be necessary for others to comprehend how an AI functions.

Additionally, the thesis contributes to advancing cognitive appraisal theory (Folkman, 2013), particularly by applying it to the domain of AI. It refines the concept of task appraisal within the AI context by delineating its two primary determinants: human-fit and AI-fit assessments. Individuals engaging in human-AI collaborations evaluate the compatibility of tasks with both human and AI capabilities. Put differently, they assess their own attributes alongside those of the AI, which can have more agency than prior technology (Baird & Maruping, 2021; Vanneste & Puranam, 2024). This assessment has a much stronger comparative character since tasks can often be completed by both entities. Moreover, this process aligns with previous studies on AI delegation, which emphasize the significance of meta-knowledge (i.e., awareness of one's own knowledge, Engelbrecht et al., 2019; Fügener et al., 2021a). Grasping this mechanism is crucial for comprehending why individuals behave in certain ways or form certain attitudes and intentions concerning AI.

7.1.3 Contributions to Research on AI Literacy Effects on Organizations and Upper Echelons Theory

Past IS research focusing on organizations has identified AI-related concepts that are crucial for an AI adoption process that creates value: Strategic AI orientation (J. Li et al., 2021) and AI implementation ability (Mikalef & Gupta, 2021; M. Weber et al., 2022). The fifth article of this thesis links research on these organizational characteristics with each other and with the stream of AI literacy research. More precisely, it contributes by empirically showing the relationship between AI value identification (achieved through AI strategy) and AI value realization (achieved through AI implementation), as well as by elucidating the role of the AI literacy of the TMT for both concepts. It shows that AI implementation ability is - directly and indirectly - affected by the AI literacy of the TMT and AI orientation. As such, the article demonstrates that AI literacy has a relevant impact beyond the individual and also needs to be considered in regard to its greater impact on organizations.

The fifth article also contributes to upper echelons theory (Hambrick, 2007; Hambrick & Mason, 1984). It introduces a skill-oriented perspective on the TMT of an organization and specifies it in the AI context in the form of TMT AI literacy. Previous upper echelons research in IS primarily relied on a role-oriented approach (e.g., J. Li et al., 2021). However, executive roles (e.g., CIO, CTO) are often ambiguously defined, which diminishes the effectiveness of this approach (Benlian & Haffke, 2016; Haffke et al., 2016). Hence, adopting a skill-oriented viewpoint is a valuable complement, allowing one to consider the person - with their unique values, experiences, and literacy - behind the role.

Furthermore, this article positions executives as a significant stakeholder group within the academic discourse. While prior studies on AI literacy have predominantly centered around users (Ng et al., 2021), they have also emphasized the stakeholder-specific nature of AI literacy, highlighting the need for the exploration of executives (Arrieta et al., 2020; Benlian, 2022). By introducing the concept of TMT AI literacy, the articles contribute to this discourse by offering a dedicated perspective on executives.

7.2 Implications for Practice

Due to the increasing adoption of AI in society and businesses, AI literacy is also a topic of high relevance to practitioners. The findings of this thesis have several implications that can be utilized for more efficient and responsible usage and management of AI in practice. Educational institutions or businesses can use the developed conceptualization of AI literacy from the first article as a reference point for setting up or reviewing their AI-related curricula, upskilling programs, or job requirements. For schools and universities, it is crucial to also provide an AI education for their non-technical students, where AI literacy might not have been integrated into the curriculum as much as for computer science students. Similarly, businesses must strategically plan which skills, knowledge, and competencies they need in their workforce in the future. This thesis' AI literacy conceptualization, with its comprehensive assessment of the proficiency dimensions and subject areas of AI literacy, can provide guidance for these challenges. By using the conceptualization, practitioners can make sure that they do not miss relevant aspects of AI literacy in their curricula, upskilling programs, or job requirements in their specific context.

Moreover, the measurement and enablement instruments for AI literacy of articles two and three of the thesis provide valuable tools for practitioners. Once an educational institution or business has defined its AI literacy strategy, it needs to be able to assess the current state of AI literacy and needs to know how to enable its respective stakeholders effectively. With the AI literacy measurement instrument from the second article, organizations can determine how literate their stakeholders are and where potential deficits lie. Then, they can leverage the enablement instrument and the design knowledge generated by the third article to develop a tailored training program for their students or employees. Moreover, the overview of learning methods concerning AI provided by the first article can further support organizations in this regard.

The insights generated by articles three, four, and five concerning the effects of AI literacy on humans and organizations also have relevant implications for practitioners. A nuanced understanding of how humans are affected when interacting or collaborating with AI and what role AI literacy plays for them can help practitioners design better human-AI collaborations. For example, knowing that a balanced understanding of the strengths and weaknesses of humans and AI is necessary for effective delegation in a specific task context informs developers and product managers to integrate the respective skills into their training or educational features. At the same time, developers need to carefully assess how to present their AI literacy educational features in order to avoid the potential negative effects of AI literacy. Concerning top management, article five has significant implications for the setup of executive roles and the management board in general. The findings indicate that successful AI adoption, which leads to value creation, is more probable when a greater number of TMT members possess AI literacy. Mandating only a single executive role (e.g., the CTO) to be AI-literate impedes AI adoption significantly. Rather, shareholders should mandate AI literacy for all executives, adapt role expectations to include AI literacy, and factor AI literacy into executive hiring considerations.

Overall, this thesis urges all kinds of practitioners – governments, schools, businesses, etc. – to thoroughly review in which of their processes AI literacy is relevant and take action to contribute to a more AI-literate society. This thesis provides concepts, tools, and knowledge that are applicable for many to start or improve their journey toward AI literacy, ultimately enabling more efficient and responsible usage and management of this new technology.

7.3 Limitations and Future Research Agenda

As with any research endeavor, this dissertation is subject to several limitations. Similarly, these limitations also provide guidance on how future research could extend the AI literacy discourse. The following reviews the core limitations of this dissertation and develops a future research agenda for AI literacy in IS research (Table 7.1).

All empirical articles in this dissertation have been conducted at a single point in time. Moreover, the articles, apart from article five, draw on experimental setups. These research design decisions allowed for the control of certain parameters and context factors. However, they also limited our findings in some regard as we do not know if the identified effects are stable over time and whether context factors from real-world settings, which have been excluded in the experimental setups, affect the identified relationships. Therefore, replicating the findings of this thesis in real-world settings would constitute a valuable extension of the discourse. Since AI literacy is a human competence-like construct, it would also be particularly interesting to see how stable such human enablement is over time. Future AI literacy studies venturing into the computer education space could employ longitudinal research designs to investigate what is necessary to sustain a particular level of AI literacy over time or if the associations between human attitudes, intentions, and behavior in human-AI collaborations and AI literacy stay stable over time (e.g., Cram et al., 2024). Moreover, it would be of interest to determine which (digital) formats are particularly suitable to convey AI literacy for which user groups. Therefore, IS research on digital learning might be a natural research stream to draw on (e.g., A. Nguyen et al., 2020).

Furthermore, the measurement of competence-like constructs is a complex topic (Weinert, 2001). The second article of the thesis developed a measurement construct based on a Likert-type scale. As such, the instrument measures "subjective AI literacy" since the participants to be measured select scores for themselves in different dimensions on scales from one to seven. In other words, the construct measures how a person subjectively judges their literacy. Moreover, the measurement instrument necessarily had to simplify certain aspects of AI literacy. The conceptualization of the first article shows the breadth and depth of AI literacy. In this regard, the thesis is limited based on the design decisions taken for the measurement construct. We urge future studies to explore different measurement methodologies and to develop measurement instruments focused on different aspects of AI literacy. Research might venture into test-based (objective) measurements (e.g., as partially employed in the third article or by P. Weber, Pinski, and Baum, 2023) or behavioral measurement approaches. More diverse measurement instruments and measurement methods would enable a more reliable and granular view of AI literacy.

The thesis could also only investigate a limited number of task and interaction types as well as instances of AI technology. Different task settings with different instances of AI technology might lead to different results. The mixed results concerning the effect of AI literacy on continuance intentions regarding AI that articles three and four found might be explained by their task, interaction, or AI type. Future studies could investigate these factors as potential moderators to shed light on this bidirectional influence of AI literacy. Therefore, this thesis invites future research focusing on human-computer interaction to explore the generalizability of this thesis' findings by identifying moderating influences to further increase our understanding of AI literacy. Furthermore, we also need a better understanding of which specific aspects of AI literacy are relevant for which kind of human-AI interaction to foster the outcomes desired in the respective situation.

IS Research Stream	Exemplary Future Research Questions Related to AI Literacy
Digital Learning and Computer Education	• How can AI literacy be acquired and sustained over time? • Which digital formats are particularly suitable to convey AI literacy for which user groups?
Measurement Methodologies	• How should an objective AI literacy measurement be constructed? • How can AI literacy be measured based on behavior?
Human-Computer Interaction	• Which factors moderate influences of AI literacy on human cognition and behavior? • Which specific aspects of AI literacy are relevant for which kind of human-AI interaction to foster the respective desired outcomes?
Information Systems Design and Development	• Which IS features can complement AI literacy to promote outcomes of interest? • How can an IS be developed to promote AI literacy?
Digital Transformation and the Future of Work	• Does AI literacy help workers cope with an AI-induced future of work that includes shifting job profiles and requirements? • How do AI-literate workers perceive digital transformation?

Table 7.1: *Future Research Agenda for AI Literacy in IS Research*

Moreover, there are other IS research streams with the potential to contribute to our understanding of AI literacy. While this thesis focuses on the human factor of AI literacy, a combination of human and technological factors can likely help us use and manage AI technology optimally. Therefore, we need to explore which technological features of an IS based on AI can complement AI literacy. Future research needs to investigate which technological features enable humans to utilize their AI literacy rather than simply nudge them in a specific direction (e.g., unengaged augmentation, Lebovitz et al., 2022). Furthermore, such studies could investigate which features can help users develop AI literacy while using such systems.

Last, AI literacy is also relevant to IS research around digital transformation and the future of work. For example, AI literacy might help workers cope with the current challenges and changes in job profiles and requirements. Future studies could investigate if and how AI literacy, with its emphasis on meta-competencies and increased awareness of the constant technological change, contributes to the agility and flexibility required from workers in the future. Moreover, one could investigate if AI-literate workers perceive the topic of digital transformation differently in general because AI literacy sensitizes workers to ethical concerns.

7.4 Conclusion

This dissertation is an attempt to enhance our understanding of AI literacy and its operationalization, as well as its impact on humans and organizations. As technology based on AI continues to influence the future of our societies and businesses, AI literacy constitutes one key factor that enables us to use this technology efficiently and responsibly. To that end, the first part of this dissertation solidified the concept of AI literacy in the emerging scientific discourse and enhanced our understanding of how to measure and enable it. The dissertation provided insights into the substance and structure of AI literacy as well as how to operationalize it purposefully for further investigation. Based on this understanding, the second part of this dissertation continued with uncovering how AI literacy affects human cognition and behavior. It could show that AI literacy has a variety of positive effects on human-AI collaboration and interaction, but it also indicates that many context factors need to be considered for optimal outcomes. Lastly, the third part of this dissertation showed that the effects of AI literacy go far beyond the individual and also have relevant implications for AI adoption in organizations. All three parts together contribute to a better understanding of the role of AI literacy in society and business. I aim for this dissertation to contribute to the momentum in the exploration of AI literacy's significance and ultimately foster more efficient and responsible human-AI collaborations and interactions in business and non-business contexts, leveraging this remarkable technology to humans' benefit.

References

Abraham, R., Schneider, J., & vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management*, *49*, 424–438. https://doi.org/10.1016/j.ijinfomgt.2019.07.008

Adam, M., Roethke, K., & Benlian, A. (2023). Human versus automated sales agents: How and why customer responses shift across sales stages. *Information Systems Research*, *34*, 1148–1168. https://doi.org/10.1287/isre.2022.1171

Adam, M., Wessel, M., & Benlian, A. (2020). Ai-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427–445. https://doi.org/10.1007/s12525-020-00414-7

Ågerfalk, P. J. (2020). Artificial intelligence as digital agency. *European Journal of Information Systems*, *29*(1), 1–8. https://doi.org/10.1080/0960085x.2020.1721947

Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for ai skills in the labor market. *Labour Economics*, *71*. https://doi.org/10.1016/j.labeco.2021.102002

Ali, S., DiPaola, D., Lee, I., Hong, J., & Breazeal, C. (2021). Exploring generative models with middle school students. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445226

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

Amazon. (2017). Tutorial: How to label thousands of images using the crowd [Retrieved August 10, 2022]. https://blog.mturk.com/tutorial-how-to-label-thousands-of-images-using-the-crowd-bea164ccbefc

Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. (2019). Guidelines for human-ai interaction. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300233

Andries, P., Debackere, K., & van Looy, B. (2013). Simultaneous experimentation as a learning strategy: Business model development under uncertainty. *Strategic Entrepreneurship Journal*, *7*(4), 288–310. https://doi.org/10.1002/sej.1170

Anton, E., Behne, A., & Teuteberg, F. (2020). The humans behind artificial intelligence - an operationalisation of ai competencies. *Proceedings of the Twenty-Eighth European Conference on Information Systems*. https://aisel.aisnet.org/ecis2020_rp/141

Arazy, O., Kumar, N., & Shapira, B. (2010). A theory-driven design framework for social recommender systems. *Journal of the Association for Information Systems*, *11*(9), 455–490. https://doi.org/10.17705/1jais.00237

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. *Information Fusion*, *58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Badal, S. B., & Ott, B. (2015). Delegating: A huge management challenge for entrepreneurs [Retrieved August 10, 2022]. https://news.gallup.com/businessjournal/182414/delegating-huge-management-challenge-entrepreneurs.aspx

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., & Zhao, J. L. (2016). Transformational issues of big data and analytics in networked business. *MIS Quarterly*, *40*(4), 807–818. https://doi.org/10.25300/misq/2016/40:4.03

Baird, A., & Maruping, L. M. (2021). The next generation of research on is use: A theoretical framework of delegation to and from agentic is artifacts. *MIS Quarterly*, *45*(1), 315–341. https://doi.org/10.25300/misq/2021/15882

Baker, T., & Nelson, R. E. (2005). Creating something from nothing: Resource construction through entrepreneurial bricolage. *Administrative Science Quarterly*, *50*, 329–366. https://doi.org/10.2189/asqu.2005.50.3.329

Bandura, A. (1986). The explanatory and predictive scope of self-efficacy theory. *Journal of Social and Clinical Psychology*, *4*(3), 359–373. https://doi.org/10.1521/jscp.1986.4.3.359

Bansal, G., Nushi, B., Kamar, E., Weld, D. S., Lasecki, W. S., & Horvitz, E. (n.d.). Update in human-ai team. understanding and addressing the performance compatibility tradeoff. *Proceedings of the Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19)*. https://doi.org/10.1609/aaai.v33i01.33012429

Bansal, G., Wu, T., Zhou, J., Fok, R., Nushi, B., Kamar, E., Ribeiro, M. T., & Weld, D. (2021). Does the whole exceed its parts? the effect of ai explanations on complementary team performance. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445717

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J Pers Soc Psychol*, *51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Bassellier, G., & Benbasat, I. (2004). Business competence of information technology professionals: Conceptual development and influence on it-business partnerships. *MIS Quarterly*, *28*(4), 673–694. https://doi.org/10.2307/25148659

Bassellier, G., Benbasat, I., & Reich, B. H. (2003). The influence of business managers' it competence on championing it. *Information Systems Research*, *14*(4), 317–336. https://doi.org/10.1287/isre.14.4.317.24899

Bassellier, G., Reich, B. H., & Benbasat, I. (2015). Information technology competence of business managers: A definition and research model. *Journal of Management Information Systems*, *17*(4), 159–182. https://doi.org/10.1080/07421222.2001.11045660

Bauer, K., von Zahn, M., & Hinz, O. (2021). Expl(ai)ned: The impact of explainable artificial intelligence on cognitive processes. *Leibniz Institute for Financial Reserach SAFE, SAFE Working Paper No. 315*. https://doi.org/10.2139/ssrn.3872711

Bauer, K., von Zahn, M., & Hinz, O. (2023). Expl(ai)ned: The impact of explainable artificial intelligence on users' information processing. *Information Systems Research*, *34*(4), 1582–1602. https://doi.org/10.1287/isre.2023.1199

Baumers, M., Dickens, P., Tuck, C., & Hague, R. (2016). The cost of additive manufacturing: Machine productivity, economies of scale and technology-push. *Technological Forecasting and Social Change*, *102*, 193–201. https://doi.org/10.1016/j.techfore.2015.02.015

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly*, *29*(3), 493–524. https://doi.org/10.2307/25148693

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. *Journal of the Association for Information Systems*, *22*(2), 281–303. https://doi.org/10.17705/1jais.00662

Benlian, A. (2022). Sprint zeal or sprint fatigue? the benefits and burdens of agile isd practices use for developer well-being. *Information Systems Research*, *33*(2), 557–578. https://doi.org/10.1287/isre.2021.1069

Benlian, A., & Haffke, I. (2016). Does mutuality matter? examining the bilateral nature and effects of ceo–cio mutual understanding. *The Journal of Strategic Information Systems*, *25*(2), 104–126. https://doi.org/10.1016/j.jsis.2016.01.001

Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmann, M., Recker, J., & Remus, U. (2022). Algorithmic management. *Business & Information Systems Engineering*, *64*, 825–839. https://doi.org/10.1007/s12599-022-00764-w

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*, *45*(3), 1433–1450. https://doi.org/10.25300/MISQ/2021/16274

Berger, B., Adam, M., Rühr, A., & Benlian, A. (2020). Watch me improve—algorithm aversion and demonstrating the ability to learn. *Business & Information Systems Engineering*, *63*(1), 55–68. https://doi.org/10.1007/s12599-020-00678-5

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, *25*(3), 351–370. https://doi.org/10.2307/3250921

Bhattacherjee, A., Davis, C. J., Connolly, A. J., Hikmet, N., Rowe, F., & Meissonier, R. (2017). User response to mandatory it use: A coping theory perspective. *European Journal of Information Systems*, *27*(4), 395–414. https://doi.org/10.1057/s41303-017-0047-0

Bobrow, D. G., & Norman, D. A. (1975). Some principles of memory schemata. In D. G. Bobrow & A. M. Collins (Eds.), *Representation and understanding: Studies in cognitive science*. Academic Press.

Bochkay, K., & Levine, C. B. (2017). Using md&a to improve earnings forecasts. *Journal of Accounting, Auditing & Finance*, *34*(3), 458–482. https://doi.org/10.1177/0148558x17722919

Bos, B., Faems, D., & Noseleit, F. (2017). Alliance concentration in multinational companies: Examining alliance portfolios, firm structure, and firm performance. *Strategic Management Journal*, *38*(11), 2298–2309. https://doi.org/10.1002/smj.2652

Bostrom, R. P., Gupta, S., & Thomas, D. (2014). A meta-theory for understanding information systems within sociotechnical systems. *Journal of Management Information Systems*, *26*(1), 17–48. https://doi.org/10.2753/mis0742-1222260102

Boudreau, M.-C., Gefen, D., & Straub, D. W. (2001). Validation in information systems research: A state-of-the-art assessment. *MIS Quarterly*, *25*(1), 1–16. https://doi.org/10.2307/3250956

Brasse, J., Broder, H. R., Förster, M., Klier, M., & Sigler, I. (2023). Explainable artificial intelligence in information systems: A review of the status quo and future research directions. *Electronic Markets*, *33*(1). https://doi.org/10.1007/s12525-023-00644-5

Brock, J. K.-U., & von Wangenheim, F. (2019). Demystifying ai: What digital transformation leaders can teach you about realistic artificial intelligence. *California Management Review*, *61*(4), 110–134. https://doi.org/10.1177/1536504219865226

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). *Generative ai at work* (Working Paper No. 31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161

Burgsteiner, H., Kandlhofer, M., & Steinbauer, G. (2016). Irobot: Teaching the basics of artificial intelligence in high schools. *Proceedings of the Sixth Symposium on Educational Advances in Artificial Intelligence (EAAI-16)*. https://doi.org/10.1609/aaai.v30i1.9864

Cai, C. J., Reif, E., Hegde, N., Hipp, J., Kim, B., Smilkov, D., Wattenberg, M., Viegas, F., Corrado, G. S., Stumpe, M. C., & Terry, M. (2019). Human-centered tools for coping with imperfect algorithms during medical decision-making. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300234

Cai, W., Jin, Y., & Chen, L. (2022). Impacts of personal characteristics on user trust in conversational recommender systems. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3517471

Cao, L. (2020). Ai in finance: A review. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3647625

Carolus, A., Augustin, Y., Markus, A., & Wienrich, C. (2023). Digital interaction literacy model – conceptualizing competencies for literate interactions with voice-based ai systems. *Computers and Education: Artificial Intelligence*, *4*. https://doi.org/10.1016/j.caeai.2022.100114

Carolus, A., Koch, M., Straka, S., Latoschik, M. E., & Wienrich, C. (2023). Mails - meta ai literacy scale: Development and testing of an ai literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies. *arXiv preprint*. https://doi.org/10.48550/arXiv.2302.09319

Carpenter, M. A., Geletkanycz, M. A., & Sanders, W. G. (2016). Upper echelons research revisited: Antecedents, elements, and consequences of top management team composition. *Journal of Management*, *30*(6), 749–778. https://doi.org/10.1016/j.jm.2004.06.001

Carroll, J. M., & Rosson, M. B. (1987). Paradox of the active user. In *Interfacing thought: Cognitive aspects of human-computer interaction.* (pp. 80–111). The MIT Press.

Carroll, N. (2021). Augmented intelligence: An actor-network theory perspective. *Proceedings of the Twenty-Ninth European Conference on Information Systems.* https://aisel.aisnet.org/ecis2021_rp/37

Casal-Otero, L., Catala, A., Fernández-Morante, C., Taboada, M., Cebreiro, B., & Barro, S. (2023). Ai literacy in k-12: A systematic literature review. *International Journal of STEM Education*, *10*(1). https://doi.org/10.1186/s40594-023-00418-7

CB Insights. (2022). The complete list of unicorn companies [Retrieved July 24, 2022]. https://www.cbinsights.com/research-unicorn-companies

Cetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B., & Knight, S. (2022). Explicating ai literacy of employees at digital workplaces. *IEEE Transactions on Engineering Management*, *71*, 810–823. https://doi.org/10.1109/tem.2021.3138503

Cetindamar, D., & Pala, O. (2011). Chief technology officer roles and performance. *Technology Analysis & Strategic Management*, *23*(10), 1031–1046. https://doi.org/10.1080/09537325.2011.621297

Chakravarty, A., Grewal, R., & Sambamurthy, V. (2013). Information technology competencies, organizational agility, and firm performance: Enabling and facilitating roles. *Information Systems Research*, *24*(4), 976–997. https://doi.org/10.1287/isre.2013.0500

Charow, R., Jeyakumar, T., Younus, S., Dolatabadi, E., Salhia, M., Al-Mouaswas, D., Anderson, M., Balakumar, S., Clare, M., Dhalla, A., Gillan, C., Haghzare, S., Jackson, E., Lalani, N., Mattson, J., Peteanu, W., Tripp, T., Waldorf, J., Williams, S., … Wiljer, D. (2021). Artificial intelligence education programs for health care professionals: Scoping review. *JMIR Med Educ*, *7*(4). https://doi.org/10.2196/31043

Chatterjee, S., Mikalef, P., Khorana, S., & Kizgin, H. (2022). Assessing the implementation of ai integrated crm system for b2c relationship management: Integrating contingency theory and dynamic capability view theory. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-022-10261-w

Chaudhury, R., Guo, P. J., & Chilana, P. K. (2022). "there's no way to keep up!": Diverse motivations and challenges faced by informal learners of ml. *Proceedings of the 2022 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*. https://doi.org/10.1109/vl/hcc53370.2022.9833100

Chen, A., Darst, P. W., & Pangrazi, R. P. (1999). What constitutes situational interest? validating a construct in physical education. *Measurement in Physical Education and Exercise Science*, *3*(3), 157–180. https://doi.org/10.1207/s15327841mpee0303_3

Chen, Chiang, & Storey. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, *36*(4), 1165–1188. https://doi.org/10.2307/41703503

Chen, D. Q., Preston, D. S., & Xia, W. (2014). Antecedents and effects of cio supply-side and demand-side leadership: A staged maturity model. *Journal of Management Information Systems*, *27*(1), 231–272. https://doi.org/10.2753/mis0742-1222270110

Cheney, P. H., Hale, D. P., & Kasper, G. M. (1990). Knowledge, skills and abilities of information systems professionals: Past, present, and future. *Information & Management*, *19*, 237–247. https://doi.org/10.1016/0378-7206(90)90033-E

Chiang, C.-W., Lu, Z., Li, Z., & Yin, M. (2023). Are two heads better than one in ai-assisted decision making? comparing the behavior and performance of groups and individuals in human-ai collaborative recidivism risk assessment. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3544548.3581015

Chiang, C.-W., & Yin, M. (2022). Exploring the effects of machine learning literacy interventions on laypeople's reliance on machine learning models. *Proceddings of the 27th International Conference on Intelligent User Interfaces*. https://doi.org/10.1145/3490099.3511121

Chiu, Y.-T., Zhu, Y.-Q., & Corbett, J. (2021). In the hearts and minds of employees: A model of pre-adoptive appraisal toward artificial intelligence in organizations. *International Journal of Information Management*, *60*. https://doi.org/10.1016/j.ijinfomgt.2021.102379

Choung, H., David, P., & Ross, A. (2022). Trust in ai and its role in the acceptance of ai technologies. *International Journal of Human–Computer Interaction*, *39*(9), 1727–1739. https://doi.org/10.1080/10447318.2022.2050543

Chung, A., Lessard, L., & Andreev, P. (2021). Information systems promoting habit formation for users: From theories to design principles. *Proceedings of the Twenty-Ninth European Conference on Information Systems*. https://aisel.aisnet.org/ecis2021_rip/18/

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology*, *100*(5), 1261–1293. https://doi.org/10.1086/230638

Cohen, J. (2016). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, *20*(1), 37–46. https://doi.org/10.1177/001316446002000104

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (Vol. 3rd). Erlbaum.

Colley, H., Hodkinson, P., & Malcolm, J. (2002). *Non-formal learning: Mapping the conceptual terrain* (Report). University of Leeds Lifelong Learning Institute. https://infed.org/mobi/non-formal-learning-mapping-the-conceptual-terrain-a-consultation-report/

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Coombs, C., Hislop, D., Taneva, S. K., & Barnard, S. (2020). The strategic impacts of intelligent automation for knowledge and service work: An interdisciplinary review. *The Journal of Strategic Information Systems*, *29*(4). https://doi.org/10.1016/j.jsis.2020.101600

Cox, A. M., & Mazumdar, S. (2022). Defining artificial intelligence for librarians. *Journal of Librarianship and Information Science*. https://doi.org/10.1177/09610006221142029

Craig, K., Thatcher, J. B., & Grover, V. (2019). The it identity threat: A conceptual definition and operational measure. *Journal of Management Information Systems*, *36*(1), 259–288. https://doi.org/10.1080/07421222.2018.1550561

Cram, W. A., D'Arcy, J., & Benlian, A. (2024). Time will tell: The case for an idiographic approach to behavioral cybersecurity research. *MIS Quarterly*, *48*(1), 95–136. https://doi.org/10.25300/MISQ/2023/17707

Cram, W. A., Proudfoot, J. G., & D'Arcy, J. (2020). When enough is enough: Investigating the antecedents and consequences of information security fatigue. *Information Systems Journal*, *31*(4), 521–549. https://doi.org/10.1111/isj.12319

Criscuolo, P., Nicolaou, N., & Salter, A. (2012). The elixir (or burden) of youth? exploring differences in innovation between start-ups and established firms. *Research Policy*, *41*(2), 319–333. https://doi.org/10.1016/j.respol.2011.12.001

Croitor, E., & Benlian, A. (2019). Perceived input control on online platforms from the application developer perspective: Conceptualisation and scale development. *Journal of Decision Systems*, *28*(1), 19–40. https://doi.org/10.1080/12460125.2019.1616977

Croteau, A.-M., & Raymond, L. (2004). Performance outcomes of strategic and it competencies alignment. *Journal of Information Technology*, *19*(3), 178–190. https://doi.org/10.1057/palgrave.jit.2000020

Dai, Y., Chai, C.-S., Lin, P.-Y., Jong, M. S.-Y., Guo, Y., & Qin, J. (2020). Promoting students' well-being by developing their readiness for the artificial intelligence age. *Sustainability*, *12*(16). https://doi.org/10.3390/su12166597

Dastin, J. (2018). Amazon scraps secret ai recruiting tool that showed bias against women [Retrieved March 27, 2023]. https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

Davenport, T., & Bean, R. (2018). Big companies are embracing analytics, but most still don't have a data-driven culture [Retrieved April 8, 2024]. *Harvard Business*

Review. https://hbr.org/2018/02/big-companies-are-embracing-analytics-but-most-still-dont-have-a-data-driven-culture

Debortoli, S., Müller, O., & vom Brocke, J. (2014). Comparing business intelligence and big data skills. *Business & Information Systems Engineering*, *6*(5), 289–300. https://doi.org/10.1007/s12599-014-0344-2

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Group.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering*, *61*(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2

Dellermann, D., Lipusch, N., Ebel, P., & Leimeister, J. M. (2018). Design principles for a hybrid intelligence decision support system for business model validation. *Electronic Markets*, *29*(3), 423–441. https://doi.org/10.1007/s12525-018-0309-2

Deming, D., & Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, *36*(S1), S337–S369. https://doi.org/10.1086/694106

Deuze, M., & Beckett, C. (2022). Imagination, algorithms and news: Developing ai literacy for journalism. *Digital Journalism*, *10*(10), 1913–1918. https://doi.org/10.1080/21670811.2022.2119152

Diederich, S., Brendel, A. B., Morana, S., & Kolbe, L. (2022). On the design of and interaction with conversational agents: An organizing and assessing review of human-computer interaction research. *Journal of the Association for Information Systems*, *23*(1), 96–138. https://doi.org/10.17705/1jais.00724

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, *64*(3), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643

Ding, F., Li, D., & George, J. F. (2014). Investigating the effects of is strategic leadership on organizational benefits from the perspective of cio strategic roles. *Information & Management*, *51*(7), 865–879. https://doi.org/10.1016/j.im.2014.08.004

Ding, X., Jiang, Y., Qin, X., Chen, Y., Zhang, W., & Qi, L. (2019). Reading face, reading health. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300435

Dolata, M., Feuerriegel, S., & Schwabe, G. (2021). A sociotechnical view of algorithmic fairness. *Information Systems Journal*, *32*(4), 754–818. https://doi.org/10.1111/isj.12370

Druga, S. (2023). *Creative ai literacies for families* [Doctoral Dissertation, University of Washington].

Druga, S., Christoph, F. L., & Ko, A. J. (2022). Family as a third space for ai literacies: How do children and parents learn about ai together? *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3502031

Druga, S., & Ko, A. J. (2021). How do children's perceptions of machine intelligence change when training and coding smart programs? *Proceedings of the 20th Annual*

ACM Interaction Design and Children Conference. https://doi.org/10.1145/3459990.3460712

Druga, S., Vu, S. T., Likhith, E., & Qiu, T. (2019). Inclusive ai literacy for kids around the world. *Proceedings of FabLearn 2019*. https://doi.org/10.1145/3311890.3311904

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Ebel, P., Söllner, M., Leimeister, J. M., Crowston, K., & de Vreede, G.-J. (2021). Hybrid intelligence in business networks. *Electronic Markets*, *31*(2), 313–318. https://doi.org/10.1007/s12525-021-00481-4

Eguchi, A., Okada, H., & Muto, Y. (2021). Contextualizing ai education for k-12 students to enhance their learning of ai literacy through culturally responsive approaches. *Künstl Intell*, *35*(2), 153–161. https://doi.org/10.1007/s13218-021-00737-3

Engel, C., Ebel, P., & Leimeister, J. M. (2022). Cognitive automation. *Electronic Markets*, *32*(1), 339–350. https://doi.org/10.1007/s12525-021-00519-7

Engelbrecht, A., Gerlach, J. P., Benlian, A., & Buxmann, P. (2019). How employees gain meta-knowledge using enterprise social networks: A validation and extension of communication visibility theory. *The Journal of Strategic Information Systems*, *28*(3), 292–309. https://doi.org/10.1016/j.jsis.2019.04.001

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2021). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, *24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Eraut, M. (2000). Non-formal learning and tacit knowledge in professional work. *Br J Educ Psychol*, *70*, 113–136. https://doi.org/10.1348/000709900158001

Eshet-Alkalai, Y. (2004). Digital literacy. *Journal of Educational Multimedia and Hypermedia*, *13*(1), 93–106.

European Commission. (2021). Artifical intelligence act [Retrieved April 8, 2024]. https://data.consilium.europa.eu/doc/document/ST-5662-2024-INIT/en/pdf

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

Falk, J. H., Storksdieck, M., & Dierking, L. D. (2016). Investigating public science interest and understanding: Evidence for the importance of free-choice learning. *Public Understanding of Science*, *16*(4), 455–469. https://doi.org/10.1177/0963662506064240

FedEx Corporation. (2022). Fedex introduces ai-powered robotic sorting arm to drive operational efficiency at its singapore hub [Retrieved August 25, 2023]. https://newsroom.fedex.com/newsroom/asia-english/fedex-introduces-ai-powered-robotic-sorting-arm-to-drive-operational-efficiency-at-its-singapore-hub

Feerrar, J. (2019). Development of a framework for digital literacy. *Reference Services Review*, *47*(2), 91–105. https://doi.org/10.1108/rsr-01-2019-0002

Fernandez Domingos, E., Terrucha, I., Suchon, R., Grujic, J., Burguillo, J. C., Santos, F. C., & Lenaerts, T. (2022). Delegation to artificial agents fosters prosocial behaviors in the collective risk dilemma. *Scientific Reports*, *12*(1), 8492. https://doi.org/10.1038/s41598-022-11518-9

Folkestad, G. (2006). Formal and informal learning situations or practices vs formal and informal ways of learning. *British Journal of Music Education*, *23*(2), 135–145. https://doi.org/10.1017/s0265051706006887

Folkman, S. (2013). Stress: Appraisal and coping. In M. Gellman & J. Turner (Eds.), *Encyclopedia of behavioral medicine*. Springer. https://doi.org/10.1007/978-1-4419-1005-9_215

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Fu, R., Tang, Y., & Chen, G. (2019). Chief sustainability officers and corporate social (ir)responsibility. *Strategic Management Journal*, *41*(4), 656–680. https://doi.org/10.1002/smj.3113

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021a). Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, *33*(2), 678–696. https://doi.org/10.1287/isre.2021.1079

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021b). Will humans-in-the-loop become borgs? merits and pitfalls of working with ai. *MIS Quarterly*, *45*(3), 1527–1556. https://doi.org/10.25300/misq/2021/16553

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative ai and chatgpt: Applications, challenges, and ai-human collaboration. *Journal of Information Technology Case and Application Research*, *25*(3), 277–304. https://doi.org/10.1080/15228053.2023.2233814

Fujiwara, T., Müller, K., & Schwarz, C. (2021). *The effect of social media on elections: Evidence from the united states* (Working Paper No. 28849). National Bureau of Economic Research. https://doi.org/10.3386/w28849

Gardiner, A., Aasheim, C., Rutner, P., & Williams, S. (2017). Skill requirements in big data: A content analysis of job advertisements. *Journal of Computer Information Systems*, *58*(4), 374–384. https://doi.org/10.1080/08874417.2017.1289354

Gefen, Rigdon, & Straub. (2011). Editor's comments: An update and extension to sem guidelines for administrative and social science research. *MIS Quarterly*, *35*(2), iii–xiv. https://doi.org/10.2307/23044042

Ghasemaghaei, M., Hassanein, K., & Benbasat, I. (2019). Assessing the design choices for online recommendation agents for older adults: Older does not always mean simpler. *MIS Quarterly*, *43*(1), 329–346. https://doi.org/10.25300/misq/2019/13947

Gilster, P. (1997). *Digital literacy*. Wiley.

Google. (2022). Advanced guide to inception v3 [Retrieved July 12, 2022]. https://cloud.google.com/tpu/docs/inception-v3-advanced

Gordon, C. (2022). Board directors and ceo ai literacy - a change imperative [Retrieved February 28, 2023]. https://www.forbes.com/sites/cindygordon/2020/08/03/why-board-directors-and-ceos-must-become-ai-literate/?sh=1ba1a7805036

Guadalupe, M., Li, H., & Wulf, J. (2014). Who lives in the c-suite? organizational structure and the division of labor in top management. *Management Science*, *60*(4), 824–844. https://doi.org/10.1287/mnsc.2013.1795

Hadash, S., Willemsen, M. C., Snijders, C., & Ijsselsteijn, W. A. (2022). Improving understandability of feature contributions in model-agnostic explainable ai tools. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3517650

Haffke, I., Kalgovas, B., & Benlian, A. (2016). The role of the cio and the cdo in an organization's digital transformation. *Proceedings of the Thirty Seventh International Conference on Information Systems*. https://aisel.aisnet.org/icis2016/ISStrategy/Presentations/3/

Hambrick, D. C. (2007). Upper echelons theory: An update. *The Academy of Management Review*, *32*(2), 334–343. https://doi.org/10.2307/20159303

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *The Academy of Management Review*, *9*(2), 193–206. https://doi.org/10.2307/258434

Hara, K., Adams, A., Milland, K., Savage, S., Callison-Burch, C., & Bigham, J. P. (2018). A data-driven analysis of workers' earnings on amazon mechanical turk. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3173574.3174023

He, G., Balayn, A., Buijsman, S., Yang, J., & Gadiraju, U. (2022). It is like finding a polar bear in the savannah! concept-level ai explanations with analogical inference from commonsense knowledge. *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*. https://doi.org/10.1609/hcomp.v10i1.21990

Heavey, C., Simsek, Z., Kyprianou, C., & Risius, M. (2020). How do strategic leaders engage with social media? a theoretical framework for research and practice. *Strategic Management Journal*, *41*(8), 1490–1527. https://doi.org/10.1002/smj.3156

Hendler, J. (2008). Avoiding another ai winter. *IEEE Intelligent Systems*, *23*(2), 2–4. https://doi.org/10.1109/mis.2008.20

Hermann, E. (2021). Artificial intelligence and mass personalization of communication content—an ethical and literacy perspective. *New Media & Society*, *24*(5), 1258–1277. https://doi.org/10.1177/14614448211022702

Herper, M. (2017). Md anderson benches ibm watson in setback for artificial intelligence in medicine [Retrieved February 2, 2023]. https://www.forbes.com/sites/matthewherper/2017/02/19/md-anderson-benches-ibm-watson-in-setback-for-artificial-intelligence-in-medicine/?sh=48f49dd13774

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, *28*(1), 75–105. https://doi.org/10.2307/25148625

Heyder, T., & Posegga, O. (2021). Extending the foundations of ai literacy. *Proceddings of the Forty-Second International Conference on Information Systems*. https://aisel.aisnet.org/icis2021/is_future_work/is_future_work/9

Holmström, B. (1979). Moral hazard and observability. *The Bell Journal of Economics*, *10*(1), 74–91. https://doi.org/10.2307/3003320

Höök, K. (2000). Steps to take before intelligent user interfaces become real. *Interacting with Computers*, *12*(4), 409–426. https://doi.org/10.1016/s0953-5438(99)00006-5

Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can ai artifacts influence human cognition? the effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management*, *56*. https://doi.org/10.1016/j.ijinfomgt.2020.102250

Huff, S. L., Maher, P. M., & Munro, M. C. (2008). Information technology and the board of directors: Is there an it attention deficit? *MIS Quarterly Executive*, *5*(2), 55–68. https://aisel.aisnet.org/misqe/vol5/iss2/3/

Hughes, A. (2023). Chatgpt: Everything you need to know about openai's gpt-4 tool [Retrieved August 8, 2023]. https://www.sciencefocus.com/future-technology/gpt-3

Hunts, A. (2021). Cto vs. cio – who do i need? [Retrieved February 28, 2023]. https://rocketloop.de/en/blog/cto-vs-cio/

Indeed.com. (2023). About indeed [Retrieved April 20, 2023]. https://www.indeed.com/about/our-company

Isaak, J., & Hanna, M. J. (2018). User data privacy: Facebook, cambridge analytica, and privacy protection. *Computer*, *51*(8), 56–59. https://doi.org/10.1109/mc.2018.3191268

Jacoby, J. (1984). Perspectives on information overload. *Journal of Consumer Research*, *10*(4), 432–435. https://doi.org/10.1086/208981

Jain, H., Padmanabhan, B., Pavlou, P. A., & Raghu, T. S. (2021). Editorial for the special section on humans, algorithms, and augmented intelligence: The future of work, organizations, and society. *Information Systems Research*, *32*(3), 675–687. https://doi.org/10.1287/isre.2021.1046

Jalili, S., Amerzadeh, M., Moosavi, S., Keshavarz, A., Zaboli, R., Tabatabaee, S. S., & Kalhor, R. (2022). Relationship between strategic orientation and performance: The mediating role of green supply chain management for better performance. *International Journal of Human Rights in Health Care*. https://doi.org/10.1108/ijhrh-03-2022-0018

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685–695. https://doi.org/10.1007/s12525-021-00475-2

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-ai symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jöhnk, J., Weißert, M., & Wyrtki, K. (2020). Ready or not, ai comes— an interview study of organizational ai readiness factors. *Business & Information Systems Engineering*, *63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Jorzik, P., Yigit, A., Kanbach, D. K., Kraus, S., & Dabić, M. (2023). Artificial intelligence-enabled business model innovation: Competencies and roles of top management. *IEEE Transactions on Engineering Management*, *71*, 7044–7056. https://doi.org/10.1109/tem.2023.3275643

Jussupow, E., Spohrer, K., Heinzl, A., & Gawlitza, J. (2021). Augmenting medical diagnosis decisions? an investigation into physicians' decision-making process with artificial intelligence. *Information Systems Research*, *32*(3), 713–735. https://doi.org/10.1287/isre.2020.0980

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, *39*(4), 341–350. https://doi.org/10.1037/0003-066x.39.4.341

Kandlhofer, M., Steinbauer, G., Hirschmugl-Gaisch, S., & Huber, P. (2016). Artificial intelligence and computer science in education: From kindergarten to university. *Proceedings of the 2016 IEEE Frontiers in Education Conference (FIE)*. https://doi.org/10.1109/FIE.2016.7757570

Kang, K., Hahn, J., & De, P. (2017). Learning effects of domain, technology, and customer knowledge in information systems development: An empirical study. *Information Systems Research*, *28*(4), 797–811. https://doi.org/10.1287/isre.2017.0713

Kapania, S., Siy, O., Clapper, G., Sp, A. M., & Sambasivan, N. (2022). "because ai is 100% right and safe": User attitudes and sources of ai authority in india. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3517533

Kaplan, A. D., Kessler, T. T., Brill, J. C., & Hancock, P. A. (2023). Trust in artificial intelligence: Meta-analytic findings. *Human Factors and Ergonomics Society*, *65*(2), 337–359. https://doi.org/10.1177/00187208211013988

Keen, P. G. W. (1991). *Shaping the future: Business design through information technology*. Harvard Business School Press.

Kent Baker, H., Pandey, N., Kumar, S., & Haldar, A. (2020). A bibliometric analysis of board diversity: Current status, development, and future research directions. *Journal of Business Research*, *108*, 232–246. https://doi.org/10.1016/j.jbusres.2019.11.025

Kerpedzhiev, G. D., König, U. M., Röglinger, M., & Rosemann, M. (2020). An exploration into future business process management capabilities in view of digitalization. *Business & Information Systems Engineering*, *63*(2), 83–96. https://doi.org/10.1007/s12599-020-00637-0

Khalid, K., Iivari, N., Kinnula, M., & Sharma, S. (2022). Familiarizing children with artificial intelligence. *Proceedings of the 25th International Academic Mindtrek Conference*. https://doi.org/10.1145/3569219.3569390

Kim, K., & Kwon, K. (2023). Exploring the ai competencies of elementary school teachers in south korea. *Computers and Education: Artificial Intelligence*, *4*. https://doi.org/10.1016/j.caeai.2023.100137

King, A. (1992). Comparison of self-questioning, summarizing, and notetaking-review as strategies for learning from lectures. *American Educational Research Journal*, *29*(2), 303–323. https://doi.org/10.3102/00028312029002303

Kitchenham, B., & Charters, S. (2007). *Guidelines for performing systematic literature reviews in software engineering* (EBSE Technical Report No. 2007-01).

Klein, K. J., & Harrison, D. A. (2007). On the diversity of diversity: Tidy logic, messier realities. *Academy of Management Perspectives*, *21*(4), 26–33. https://doi.org/10.5465/amp.2007.27895337

Klerck, D., & Sweeney, J. C. (2007). The effect of knowledge types on consumer-perceived risk and adoption of genetically modified foods. *Psychology and Marketing*, *24*(2), 171–193. https://doi.org/10.1002/mar.20157

Knoth, N., Decker, M., Laupichler, M. C., Pinski, M., Buchholtz, N., Bata, K., & Schultz, B. (2024). Developing a holistic ai literacy assessment matrix – bridging generic, domain-specific, and ethical competencies. *Computers and Education Open*, *6*. https://doi.org/10.1016/j.caeo.2024.100177

Kocielnik, R., Amershi, S., & Bennett, P. N. (2019). Will you accept an imperfect ai? *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300641

Kohler, T. (2016). Corporate accelerators: Building bridges between corporations and startups. *Business Horizons*, *59*(3), 347–357. https://doi.org/10.1016/j.bushor.2016.01.008

Kong, S.-C., Man-Yin Cheung, W., & Zhang, G. (2021). Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. *Computers and Education: Artificial Intelligence*, *2*. https://doi.org/10.1016/j.caeai.2021.100026

Kortum, H., Rebstadt, J., & Thomas, O. (2022). Dissection of ai job advertisements: A text mining-based analysis of employee skills in the disciplines computer vision and natural language processing. *Proceedings of the 55th Hawaii International Conference on System Sciences*. https://doi.org/10.24251/hicss.2022.635

Kraiger, K., Ford, J. K., & Salas, E. (1993). Application of cognitive, skill-based, and affective theories of learning outcomes to new methods of training evaluation. *Journal of Applied Psychology*, *78*(2), 311–328. https://doi.org/10.1037/0021-9010.78.2.311

Krath, J., Schürmann, L., & von Korflesch, H. F. O. (2021). Revealing the theoretical basis of gamification: A systematic review and analysis of theory in research on gamification, serious games and game-based learning. *Computers in Human Behavior*, *125*. https://doi.org/10.1016/j.chb.2021.106963

Krathwohl, D. R. (2010). A revision of bloom's taxonomy: An overview. *Theory Into Practice*, *41*(4), 212–218. https://doi.org/10.1207/s15430421tip4104_2

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*, *77*(6), 1121–1134. https://doi.org/10.1037//0022-3514.77.6.1121

Kruse, L., Wunderlich, N., & Beck, R. (2019). Artificial intelligence for the financial services industry: What challenges organizations to succeed. *Proceedings of the 52nd Hawaii International Conference on System Sciences*. http://hdl.handle.net/10125/60075

Kuechler, W., & Vaishnavi, V. (2012). A framework for theory development in design science research: Multiple perspectives. *Journal of the Association for Information Systems*, *13*(6), 395–423. https://doi.org/10.17705/1jais.00300

Kusuma, M., Mohanty, V., Wang, M., & Luther, K. (2022). Civil war twin. *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*. https://doi.org/10.1145/3514094.3534141

Lai, V., Carton, S., Bhatnagar, R., Liao, Q. V., Zhang, Y., & Tan, C. (2022). Human-ai collaboration via conditional delegation: A case study of content moderation. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3501999

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174. https://doi.org/10.2307/2529310

Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. (2023). Development of the "scale for the assessment of non-experts' ai literacy" – an exploratory factor analysis. *Computers in Human Behavior Reports*, *12*. https://doi.org/10.1016/j.chbr.2023.100338

Laupichler, M. C., Aster, A., & Raupach, T. (2023). Delphi study for the development and preliminary validation of an item set for the assessment of non-experts' ai literacy. *Computers and Education: Artificial Intelligence*, *4*. https://doi.org/10.1016/j.caeai.2023.100126

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

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal and coping*. Springer.

Leana, C. R. (1986). Predictors and consequences of delegation. *Academy of Management Journal*, *29*(4), 754–774. https://doi.org/10.2307/255943

Leana, C. R. (1987). Power relinquishment versus power sharing: Theoretical clarification and empirical comparison of delegation and participation. *Journal of Applied Psychology*, *72*(2), 228–233. https://doi.org/10.1037/0021-9010.72.2.228

Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with ai for critical judgments: How professionals deal with opacity when using ai for medical diagnosis. *Organization Science*, *33*(1), 126–148. https://doi.org/10.1287/orsc.2021.1549

Lee, I., & Shin, Y. J. (2018). Fintech: Ecosystem, business models, investment decisions, and challenges. *Business Horizons*, *61*(1), 35–46. https://doi.org/10.1016/j.bushor.2017.09.003

Lee, I., Ali, S., Zhang, H., DiPaola, D., & Breazeal, C. (2021). Developing middle school students' ai literacy. *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*. https://doi.org/10.1145/3408877.3432513

Lee, I., Zhang, H., Moore, K., Zhou, X., Perret, B., Cheng, Y., Zheng, R., & Pu, G. (2022). Ai book club. *Proceedings of the 53rd ACM Technical Symposium on Computer Science Education*. https://doi.org/10.1145/3478431.3499318

Lee, M., & Park, J.-S. (2022). Do parasocial relationships and the quality of communication with ai shopping chatbots determine middle-aged women consumers' continuance usage intentions? *Journal of Consumer Behaviour*, *21*(4), 842–854. https://doi.org/10.1002/cb.2043

Leichtmann, B., Humer, C., Hinterreiter, A., Streit, M., & Mara, M. (2023). Effects of explainable artificial intelligence on trust and human behavior in a high-risk decision task. *Computers in Human Behavior*, *139*. https://doi.org/10.1016/j.chb.2022.107539

Lepak, D. P., & Snell, S. A. (1999). The human resource architecture: Toward a theory of human capital allocation and development. *The Academy of Management Review*, *24*(1), 31–48. https://doi.org/10.2307/259035

Leppänen, P., George, G., & Alexy, O. (2023). When do novel business models lead to high performance? a configurational approach to value drivers, competitive strategy, and firm environment. *Academy of Management Journal*, *66*(1), 164–194. https://doi.org/10.5465/amj.2020.0969

Leu, D. J., Kinzer, C. K., Coiro, J., Castek, J., & Henry, L. A. (2013). New literacies: A dual-level theory of the changing nature of literacy, instruction, and assessment. *Journal of Education*, *197*(2), 1–18. https://doi.org/10.1177/002205741719700202

Leu, D. J., Kinzer, C. K., Coiro, J. L., & Cammack, D. W. (2004). Toward a theory of new literacies emerging from the internet and other information and communication technologies. In R. Ruddell & N. Unrau (Eds.), *Theoretical models and processes of reading* (pp. 1570–1613, Vol. 5).

Li, J., Li, M., Wang, X., & Bennett Thatcher, J. (2021). Strategic directions for ai: The role of cios and boards of directors. *MIS Quarterly*, *45*(3), 1603–1644. https://doi.org/10.25300/misq/2021/16523

Li, Y., Wei, Z., & Liu, Y. (2010). Strategic orientations, knowledge acquisition, and firm performance: The perspective of the vendor in cross-border outsourcing. *Journal of Management Studies*, *47*(8), 1457–1482. https://doi.org/10.1111/j.1467-6486.2010.00949.x

Liang, C., Proft, J., Andersen, E., & Knepper, R. A. (2019). Implicit communication of actionable information in human-ai teams. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300325

Liao, Q. V., Gruen, D., & Miller, S. (2020). Questioning the ai: Informing design practices for explainable ai user experiences. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3313831.3376590

LinkedIn.com. (2023). About linkedin [Retrieved April 19, 2023]. https://about.linkedin.com/

Liu, D., Santhanam, R., & Webster, J. (2017). Toward meaningful engagement: A framework for design and research of gamified information systems. *MIS Quarterly*, *41*(4), 1011–1034. https://doi.org/10.25300/misq/2017/41.4.01

Liu, S., & Xie, X. (2021). Ai quality cultivation and application ability training for normal university students. *Proceedings of the 2021 7th Annual International Conference on Network and Information Systems for Computers (ICNISC)*. https://doi.org/10.1109/icnisc54316.2021.00030

Livingstone, S. (2004). Media literacy and the challenge of new information and communication technologies. *The Communication Review*, *7*(1), 3–14. https://doi.org/10.1080/10714420490280152

Long, D. (2023). Conducting remote design research on embodied, collaborative museum exhibits. *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3544549.3573842

Long, D., Blunt, T., & Magerko, B. (2021). Co-designing ai literacy exhibits for informal learning spaces. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–35. https://doi.org/10.1145/3476034

Long, D., Jacob, M., & Magerko, B. (2019). Designing co-creative ai for public spaces. *Proceedings of the 2019 on Creativity and Cognition*. https://doi.org/10.1145/3325480.3325504

Long, D., & Magerko, B. (2020). What is ai literacy? competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3313831.3376727

Long, D., Padiyath, A., Teachey, A., & Magerko, B. (2021). The role of collaboration, creativity, and embodiment in ai learning experiences. *Proceedings of the 2021 on Creativity and Cognition*. https://doi.org/10.1145/3450741.3465264

Long, D., Teachey, A., & Magerko, B. (2022). Family learning talk in ai literacy learning activities. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 1–20. https://doi.org/10.1145/3491102.3502091

Lubars, B., & Tan, C. (2019). Ask not what ai can do, but what ai should do: Towards a framework of task delegability. *Proceedings of the 33rd Conference on Neural Information Processing Systems*. https://doi.org/10.48550/arXiv.1902.03245

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in mis and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, *35*(2), 293–334. https://doi.org/10.2307/23044045

Maitz, K., Fessl, A., Pammer-Schindler, V., Kaiser, R., & Lindstaedt, S. (2022). What do construction workers know about artificial intelligence? an exploratory case study in an austrian sme. *Proceedings of the Mensch und Computer 2022*. https://doi.org/10.1145/3543758.3547545

Malhotra, N. K. (1982). Information load and consumer decision making. *Journal of Consumer Research*, *8*(4), 419–430. https://doi.org/10.1086/208882

Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (iuipc): The construct, the scale, and a causal model. *Information Systems Research*, *15*(4), 336–355. https://doi.org/10.1287/isre.1040.0032

Manuti, A., Pastore, S., Scardigno, A. F., Giancaspro, M. L., & Morciano, D. (2015). Formal and informal learning in the workplace: A research review. *International*

Journal of Training and Development, *19*(1), 1–17. https://doi.org/10.1111/ijtd.12044

Marcolin, B. L., Compeau, D. R., Munro, M. C., & Huff, S. L. (2000). Assessing user competence: Conceptualization and measurement. *Information Systems Research*, *11*(1), 37–60. https://doi.org/10.1287/isre.11.1.37.11782

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

Markus, M. L. (2017). Datification, organizational strategy, and is research: What's the score? *The Journal of Strategic Information Systems*, *26*(3), 233–241. https://doi.org/10.1016/j.jsis.2017.08.003

Marsick, V. J., & Watkins, K. E. (2001). Informal and incidental learning. *New Directions for Adult and Continuing Education*, *2001*(89), 25–34. https://doi.org/10.1002/ace.5

Mattke, J., Müller, L., & Maier, C. (2019). Paid, owned and earned media: A qualitative comparative analysis revealing attributes influencing consumer's brand attitude in social media. *Proceedings of the 52nd Hawaii International Conference on System Sciences*. http://hdl.handle.net/10125/59520

McCabe, C. J., Kim, D. S., & King, K. M. (2018). Improving present practices in the visual display of interactions. *Adv Methods Pract Psychol Sci*, *1*(2), 147–165. https://doi.org/10.1177/2515245917746792

McCarthy, J. L., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). A proposal for the dartmouth summer research project on artificial intelligence [Retrieved April 9, 2024]. http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf

McNeese, N. J., Schelble, B. G., Canonico, L. B., & Demir, M. (2021). Who/what is my teammate? team composition considerations in human–ai teaming. *IEEE Transactions on Human-Machine Systems*, *51*(4), 288–299. https://doi.org/10.1109/thms.2021.3086018

Melsión, G. I., Torre, I., Vidal, E., & Leite, I. (2021). Using explainability to help children understandgender bias in ai. *Proceedings of the Interaction Design and Children*. https://doi.org/10.1145/3459990.3460719

Merriam-Webster. (2023). Definition awareness [Retrieved August 9, 2023]. https://www.merriam-webster.com/dictionary/awareness

Meske, C., Bunde, E., Schneider, J., & Gersch, M. (2020). Explainable artificial intelligence: Objectives, stakeholders, and future research opportunities. *Information Systems Management*, *39*(1), 53–63. https://doi.org/10.1080/10580530.2020.1849465

Mikalef, P., Conboy, K., Lundström, J. E., & Popovič, A. (2022). Thinking responsibly about responsible ai and 'the dark side' of ai. *European Journal of Information Systems*, *31*(3), 257–268. https://doi.org/10.1080/0960085x.2022.2026621

Mikalef, P., Fjørtoft, S. O., & Torvatn, H. Y. (2019). Developing an artificial intelligence capability: A theoretical framework for business value. In W. Abramowicz & R. Corchuelo (Eds.), *Business information systems workshops* (pp. 409–416). Springer International Publishing.

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

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., Gupta, M., & Niehaves, B. (2022). Enabling ai capabilities in government agencies: A study of determinants for european municipalities. *Government Information Quarterly*, *39*(4). https://doi.org/10.1016/j.giq.2021.101596

Miles, M. P., & Arnold, D. R. (2017). The relationship between marketing orientation and entrepreneurial orientation. *Entrepreneurship Theory and Practice*, *15*(4), 49–66. https://doi.org/10.1177/104225879101500407

Milewski, A. E., & Lewis, S. H. (1997). Delegating to software agents. *International Journal of Human-Computer Studies*, *46*(4), 485–500. https://doi.org/10.1006/ijhc.1996.0100

Milmo, D. (2023). Chatgpt reaches 100 million users two months after launch [Retrieved July 25, 2023]. https://www.theguardian.com/technology/2023/feb/02/chatgpt-100-million-users-open-ai-fastest-growing-app

Mohiuddin Babu, M. (2017). Impact of firm's customer orientation on performance: The moderating role of interfunctional coordination and employee commitment. *Journal of Strategic Marketing*, *26*(8), 702–722. https://doi.org/10.1080/0965254x.2017.1384037

Moore, D. R. (2010). Technology literacy: The extension of cognition. *International Journal of Technology and Design Education*, *21*(2), 185–193. https://doi.org/10.1007/s10798-010-9113-9

Moore, F. G. (1982). *The management of organizations*. Wiley.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Murray, A., Rhymer, J., & Sirmon, D. G. (2021). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, *46*(3), 552–571. https://doi.org/10.5465/amr.2019.0186

NAICS. (2023). North american industry classification system (by u.s. census bureau) [Retrieved July 31, 2023]. https://www.census.gov/naics/

Naranjo-Gil, D. (2009). Management information systems and strategic performances: The role of top team composition. *International Journal of Information Management*, *29*(2), 104–110. https://doi.org/10.1016/j.ijinfomgt.2008.05.009

Navarro, J., Allali, S., Cabrignac, N., & Cegarra, J. (2021). Impact of pilot's expertise on selection, use, trust, and acceptance of automation. *IEEE Transactions on Human-Machine Systems*, *51*(5), 432–441. https://doi.org/10.1109/thms.2021.3090199

Neumann, M. M., Finger, G., & Neumann, D. L. (2016). A conceptual framework for emergent digital literacy. *Early Childhood Education Journal*, *45*(4), 471–479. https://doi.org/10.1007/s10643-016-0792-z

Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes*, *160*, 149–167. https://doi.org/10.1016/j.obhdp.2020.03.008

Neyer, F., Felber, J., & Gebhardt, C. (2016). Kurzskala zur erfassung von technikbereitschaft (technology commitment). *Zusammenstellung sozialwissenschaftlicher Items und Skalen (ZIS)*. https://doi.org/10.6102/zis244

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing ai literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, *2*. https://doi.org/10.1016/j.caeai.2021.100041

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

Nguyen, A., Hong, Y., & Gardner, L. A. (2020). A taxonomy of digital learning activities for digital inclusion. *Proceedings of the Twenty-Eighth European Conference on Information Systems*. https://aisel.aisnet.org/ecis2020_rp/135

Nguyen, Q. N., Sidorova, A., & Torres, R. (2022). Artificial intelligence in business: A literature review and research agenda. *Communications of the Association for Information Systems*, *50*, 175–207. https://doi.org/10.17705/1cais.05007

Nguyen, T. H., Paasche-Orlow, M. K., & McCormack, L. A. (2017). The state of the science of health literacy measurement. *Information Services & Use*, *37*(2), 189–203. https://doi.org/10.3233/isu-170827

Ninaus, M., Moeller, K., McMullen, J., & Kiili, K. (2017). Acceptance of game-based learning and intrinsic motivation as predictors for learning success and flow experience. *International Journal of Serious Games*, *4*(3). https://doi.org/10.17083/ijsg.v4i3.176

Njenga, J. K. (2018). Digital literacy: The quest of an inclusive definition. *Reading & Writing*, *9*(1). https://doi.org/10.4102/rw.v9i1.183

Nomura, T., Suzuki, T., Kanda, T., & Kato, K. (2006). Measurement of negative attitudes toward robots. *Interaction Studies*, *7*(3), 437–454. https://doi.org/10.1075/is.7.3.14nom

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science*, *5*(1), 14–37. http://www.jstor.com/stable/2635068

Norkute, M., Herger, N., Michalak, L., Mulder, A., & Gao, S. (2021). Towards explainable ai: Assessing the usefulness and impact of added explainability features in legal document summarization. *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411763.3443441

Norman, C. D., & Skinner, H. A. (2006). Eheals: The ehealth literacy scale. *J Med Internet Res*, *8*(4). https://doi.org/10.2196/jmir.8.4.e27

Ocasio, W. (1997). Towards an attention-based view of the firm. *Strategic Management Journal*, *18*(S1), 187–206. https://doi.org/10.1002/(sici)1097-0266(199707)18:1+⟨187::Aid-smj936⟩3.0.Co;2-k

Ocasio, W. (2011). Attention to attention. *Organization Science*, *22*(5), 1286–1296. https://doi.org/10.1287/orsc.1100.0602

OECD. (2019). *The survey of adult skills: Reader's companion* (Report). OECD Publishing. https://doi.org/10.1787/f70238c7-en

Oehmichen, J., Schult, A., & Dong, J. Q. (2023). Successfully organizing ai innovation through collaboration with startups. *MIS Quarterly Executive*, *22*(1). https://aisel.aisnet.org/misqe/vol22/iss1/4

Olari, V., & Romeike, R. (2021). Addressing ai and data literacy in teacher education: A review of existing educational frameworks. *Proceedings of the 16th Workshop in Primary and Secondary Computing Education*. https://doi.org/10.1145/3481312.3481351

Ongena, G. (2023). Data literacy for improving governmental performance: A competence-based approach and multidimensional operationalization. *Digital Business*, *3*(1). https://doi.org/10.1016/j.digbus.2022.100050

Oppong-Tawiah, D., Webster, J., Staples, S., Cameron, A.-F., Ortiz de Guinea, A., & Hung, T. Y. (2020). Developing a gamified mobile application to encourage sustainable energy use in the office. *Journal of Business Research*, *106*, 388–405. https://doi.org/10.1016/j.jbusres.2018.10.051

Ortiz, S. (2023). Chatgpt's hallucination just got openaisued. here's what happened [Retrieved July 25, 2023]. https://www.zdnet.com/article/chatgpts-hallucination-just-got-openai-sued-heres-what-happened/

Palan, S., & Schitter, C. (2018). Prolific.ac—a subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22–27. https://doi.org/10.1016/j.jbef.2017.12.004

Papagiannidis, E., Merete Enholm, I., Mikalef, P., & Krogstie, J. (2021). Structuring ai resources to build an ai capability: A conceptual framework. *Proceedings of the Twenty-Ninth European Conference on Information Systems*. https://aisel.aisnet.org/ecis2021_rip/47/

Papert, S. (1993). *Mindstorms: Children, computers, and powerful ideas* (2nd). Basic Books.

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

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2014). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/mis0742-1222240302

Peifer, Y., Jeske, T., & Hille, S. (2022). Artificial intelligence and its impact on leaders and leadership. *Procedia Computer Science*, *200*, 1024–1030. https://doi.org/10.1016/j.procs.2022.01.301

Peng, B., Galley, M., He, P., Cheng, H., Xie, Y., Hu, Y., Huang, Q., Liden, L., Yu, Z., & Chen, W. (2023). Check your facts and try again: Improving large language models with external knowledge and automated feedback. *arXiv preprint*. https://doi.org/10.48550/arXiv.2302.12813

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of ai on developer productivity: Evidence from github copilot. *arXiv preprint*. https://doi.org/10.48550/arXiv.2302.06590

Peppard, J., Edwards, C., & Lambert, R. (2011). Clarifying the ambiguous role of the cio. *MIS Quarterly Executive*, *10*(1). https://aisel.aisnet.org/misqe/vol10/iss1/3

Pigola, A., da Costa, P. R., van der Poel, N., & Yamaçake, F. T. R. (2022). New perspectives for dynamic capabilities in meeting needs of startups' survival. *Journal of Entrepreneurship in Emerging Economies*. https://doi.org/10.1108/jeee-06-2021-0258

Pillay, N., Maharaj, B. T., & van Eeden, G. (2018). Ai in engineering and computer science education in preparation for the 4th industrial revolution: A south african perspective. *Proceedings of the 2018 World Engineering Education Forum - Global Engineering Deans Council*. https://doi.org/10.1109/WEEF-GEDC.2018.8629703

Pinski, M., Adam, M., & Benlian, A. (2023). Ai knowledge: Improving ai delegation through human enablement. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3544548.3580794

Pinski, M., & Benlian, A. (2023). Ai literacy - towards measuring human competency in artificial intelligence. *Proceedings of the 56th Hawaii International Conference on System Sciences*. https://hdl.handle.net/10125/102649

Pinski, M., & Benlian, A. (2024). Ai literacy for users – a comprehensive review and future research directions of learning methods, components, and effects. *Computers in Human Behavior: Artificial Humans*, *2*(1). https://doi.org/10.1016/j.chbah.2024.100062

Pinski, M., Haas, M., & Benlian, A. (2024). Building metaknowledge in ai literacy – the effect of gamified vs. text-based learning on ai literacy metaknowledge. *Proceedings of the 57th Hawaii International Conference on System Sciences*. https://hdl.handle.net/10125/107004

Pinski, M., Haas, M., & Franz, A. (2023). Ailingo – a design science approach to advancing non-expert adults' ai literacy. *Proceedings of the Forty-Fourth International Conference on Information Systems*. https://aisel.aisnet.org/icis2023/learnandiscurricula/learnandiscurricula/10

Pinski, M., Hofmann, T., & Benlian, A. (2023). Executive ai literacy: A text-mining approach to understand existing and demanded ai skills of leaders in unicorn firms. *Proceedings of the Wirtschaftsinformatik 2023*. https://aisel.aisnet.org/wi2023/7

Pinski, M., Hofmann, T., & Benlian, A. (2024). Ai literacy for the top management: An upper echelons perspective on corporate ai orientation and implementation ability. *Electronic Markets*, *34*(1). https://doi.org/10.1007/s12525-024-00707-1

Pinski, M., Tarafdar, M., & Benlian, A. (2024). Why executives can't get comfortable with ai. *MIT Sloan Management Review*. https://sloanreview.mit.edu/article/why-executives-cant-get-comfortable-with-ai/#article-authors

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2016). Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences. *Organizational Research Methods*, *19*(2), 159–203. https://doi.org/10.1177/1094428115624965

Potter, W. J. (2004). *Theory of media literacy: A cognitive approach*. SAGE Publications, Inc. https://doi.org/10.4135/9781483328881

Potter, W. J. (2013). Review of literature on media literacy. *Sociology Compass*, *7*(6), 417–435. https://doi.org/10.1111/soc4.12041

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence - exploring organizational readiness factors. *Twenty-Seventh European Conference on Information Systems*. https://aisel.aisnet.org/ecis2019_rp/106/

Rai, A., Brown, P., & Tang, X. (2014). Organizational assimilation of electronic procurement innovations. *Journal of Management Information Systems*, *26*(1), 257–296. https://doi.org/10.2753/mis0742-1222260110

Rai, A., Constantinides, P., & Sarker, S. (2019). Next-generation digital platforms: Toward human–ai hybrids. *MIS Quarterly*, *43*(1), iii–x. https://misq.umn.edu/misq/downloads/download/editorial/687/

Ramamurthy, K., Sen, A., & Sinha, A. P. (2008). An empirical investigation of the key determinants of data warehouse adoption. *Decision Support Systems*, *44*(4), 817–841. https://doi.org/10.1016/j.dss.2007.10.006

Rana, G., & Sharma, R. (2019). Emerging human resource management practices in industry 4.0. *Strategic HR Review*, *18*(4), 176–181. https://doi.org/10.1108/shr-01-2019-0003

Rana, N. P., Chatterjee, S., Dwivedi, Y. K., & Akter, S. (2021). Understanding dark side of artificial intelligence (ai) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. *European Journal of Information Systems*, *31*(3), 364–387. https://doi.org/10.1080/0960085x.2021.1955628

Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., & Kiron, D. (2019). Winning with ai. *MIT Sloan Management Review and Boston Consulting Group*. https://sloanreview.mit.edu/projects/winning-with-ai/

Rao, Q., & Frtunikj, J. (2018). Deep learning for self-driving cars. *Proceedings of the 1st International Workshop on Software Engineering for AI in Autonomous Systems*. https://doi.org/10.1145/3194085.3194087

Register, Y., & Ko, A. J. (2020). Learning machine learning with personal data helps stakeholders ground advocacy arguments in model mechanics. *Proceedings of the 2020 ACM Conference on International Computing Education Research*. https://doi.org/10.1145/3372782.3406252

Reis, C., Ruivo, P., Oliveira, T., & Faroleiro, P. (2020). Assessing the drivers of machine learning business value. *Journal of Business Research*, *117*, 232–243. https://doi.org/10.1016/j.jbusres.2020.05.053

Roepke, R., Agarwal, R., & Ferratt, T. W. (2000). Aligning the it human resource with business vision: The leadership initiative at 3m. *MIS Quarterly*, *24*(2), 327–353. https://doi.org/10.2307/3250941

Romanko, O., & O'Mahony, M. (2022). *The use of online job sites for measuring skills and labour market trends: A review* (ESCoE Technical Report TR-19). Economic Statistics Centre of Excellence - National Institute of Economic and Social Research.

Rothaermel, F. T., & Deeds, D. L. (2004). Exploration and exploitation alliances in biotechnology: A system of new product development. *Strategic Management Journal*, *25*(3), 201–221. https://doi.org/10.1002/smj.376

Royer, J. M. (1979). Theories of the transfer of learning. *Educational Psychologist*, *14*(1), 53–69. https://doi.org/10.1080/00461527909529207

Ruoff, M., Gnewuch, U., Maedche, A., & Scheibehenne, B. (2021). Designing conversational dashboards for effective use in crisis response. *Journal of the Association for Information Systems*, *21*(1), 247–265. https://doi.org/10.17705/1jais.00491

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemp Educ Psychol*, *25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020

Sailer, M., & Homner, L. (2019). The gamification of learning: A meta-analysis. *Educational Psychology Review*, *32*(1), 77–112. https://doi.org/10.1007/s10648-019-09498-w

Salazar-Gomez, A. F., Bagiati, A., Minicucci, N., Kennedy, K. D., Du, X., & Breazeal, C. (2022). Designing and implementing an ai education program for learners with diverse background at scale. *Proceedings of the 2022 IEEE Frontiers in Education Conference (FIE)*. https://doi.org/10.1109/fie56618.2022.9962632

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS Quarterly*, *27*(2), 237–263. https://doi.org/10.2307/30036530

Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021). "everyone wants to do the model work, not the data work": Data cascades in high-stakes ai. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445518

Sarker, S., Chatterjee, S., Xiao, X., & Elbanna, A. (2019). The sociotechnical axis of cohesion for the is discipline: Its historical legacy and its continued relevance. *MIS Quarterly*, *43*(3), 695–719. https://doi.org/10.25300/misq/2019/13747

Schecter, A., Bogert, E., & Lauharatanahirun, N. (2023). Algorithmic appreciation or aversion? the moderating effects of uncertainty on algorithmic decision making. *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3544549.3585908

Schepman, A., & Rodway, P. (2022). The general attitudes towards artificial intelligence scale (gaais): Confirmatory validation and associations with personality, corporate distrust, and general trust. *International Journal of Human–Computer Interaction*, (39), 2724–2741. https://doi.org/10.1080/10447318.2022.2085400

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, *29*(4), 260–278. https://doi.org/10.1080/12460125.2020.1819094

Schneider, J., Meske, C., & Bikic, A. (2023). How individuals can shape ai through data - an ai literacy and morality perspective. *Proceedings of the Thirty-first European Conference on Information Systems*. https://aisel.aisnet.org/ecis2023_rp/368

Schoeffer, J., Kuehl, N., & Machowski, Y. (2022). “there is not enough information”: On the effects of explanations on perceptions of informational fairness and trustworthiness in automated decision-making. *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. https://doi.org/10.1145/3531146.3533218

Schryen, G., Wagner, G., Benlian, A., & Paré, G. (2021). A knowledge development perspective on literature reviews: Validation of a new typology in the is field. *Communications of the Association for Information Systems*, *49*(1), 134–186. https://doi.org/10.17705/1cais.04607

Schuetz, S., & Venkatesh, V. (2020). Research perspectives: The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *Journal of the Association for Information Systems*, *21*(2), 460–482. https://doi.org/10.17705/1jais.00608

Schulte, A., Donath, D., & Lange, D. S. (2016). Design patterns for human-cognitive agent teaming. In D. Harris (Ed.), *Engineering psychology and cognitive ergonomics*. Springer. https://doi.org/10.1007/978-3-319-40030-3_24

Schunk, D. H. (2012). *Learning theories - an educational perspective* (6th). Pearson.

Scuik, C., & Hess, T. (2022). Governing digital transformation – the profiles of top managers. *Proceedings of the Pacific Asia Conference on Information Systems 2022*. https://aisel.aisnet.org/pacis2022/28

Selwyn, N., & Gallo Cordoba, B. (2021). Australian public understandings of artificial intelligence. *Ai & Society*, *37*(4), 1645–1662. https://doi.org/10.1007/s00146-021-01268-z

Shen, H., Liao, K., Liao, Z., Doornberg, J., Qiao, M., van den Hengel, A., & Verjans, J. W. (2021). Human-ai interactive and continuous sensemaking: A case study of image classification using scribble attention maps. *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411763.3451798

Shollo, A., Hopf, K., Thiess, T., & Müller, O. (2022). Shifting ml value creation mechanisms: A process model of ml value creation. *The Journal of Strategic Information Systems*, *31*(3). https://doi.org/10.1016/j.jsis.2022.101734

Sidorova, Evangelopoulos, Valacich, & Ramakrishnan. (2008). Appendix: Uncovering the intellectual core of the information systems discipline. *MIS Quarterly*, *32*(3), 467–482. https://doi.org/10.2307/25148852

Silic, M., & Lowry, P. B. (2020). Using design-science based gamification to improve organizational security training and compliance. *Journal of Management Information Systems*, *37*(1), 129–161. https://doi.org/10.1080/07421222.2019.1705512

Simon, H. A. (1990). Bounded rationality. In J. Eatwell, M. Milgate, & P. Newman (Eds.), *Utility and probability*. Palgrave Macmillan. https://doi.org/10.1007/978-1-349-20568-4_5

Simons, T., Pelled, L. H., & Smith, K. A. (1999). Making use of difference: Diversity, debate, and decision comprehensiveness in top management teams. *Academy of Management Journal*, *42*(6), 662–673. https://doi.org/10.2307/256987

Sindermann, C., Sha, P., Zhou, M., Wernicke, J., Schmitt, H. S., Li, M., Sariyska, R., Stavrou, M., Becker, B., & Montag, C. (2020). Assessing the attitude towards artificial intelligence: Introduction of a short measure in german, chinese, and english language. *KI - Künstliche Intelligenz*, *35*(1), 109–118. https://doi.org/10.1007/s13218-020-00689-0

Sobol, M. G., & Klein, G. (2009). Relation of cio background, it infrastructure, and economic performance. *Information & Management*, *46*(5), 271–278. https://doi.org/10.1016/j.im.2009.05.001

Someh, I., Davern, M., Breidbach, C. F., & Shanks, G. (2019). Ethical issues in big data analytics: A stakeholder perspective. *Communications of the Association for Information Systems*, *44*(1), 718–747. https://doi.org/10.17705/1cais.04434

Spiekermann, S., Krasnova, H., Hinz, O., Baumann, A., Benlian, A., Gimpel, H., Heimbach, I., Köster, A., Maedche, A., Niehaves, B., Risius, M., & Trenz, M. (2022). Values and ethics in information systems. *Business & Information Systems Engineering*, *64*(2), 247–264. https://doi.org/10.1007/s12599-021-00734-8

Stanford Vision Labs. (2022). Imagenet [Retrieved July 12, 2022]. https://www.image-net.org/index.php

Steiber, A., & Alänge, S. (2020). Corporate-startup collaboration: Effects on large firms' business transformation. *European Journal of Innovation Management*, *24*(2), 235–257. https://doi.org/10.1108/ejim-10-2019-0312

Steinbauer, G., Kandlhofer, M., Chklovski, T., Heintz, F., & Koenig, S. (2021). A differentiated discussion about ai education k-12. *KI - Künstliche Intelligenz*, *35*(2), 131–137. https://doi.org/10.1007/s13218-021-00724-8

Stjernfelt, F., & Lauritzen, A. M. (2020). Facebook's handbook of content removal. In *Your post has been removed: Tech giants and freedom of speech* (pp. 115–137). Springer International Publishing. https://doi.org/10.1007/978-3-030-25968-6_11

Su, J., Ng, D. T. K., & Chu, S. K. W. (2023). Artificial intelligence (ai) literacy in early childhood education: The challenges and opportunities. *Computers and Education: Artificial Intelligence*, *4*. https://doi.org/10.1016/j.caeai.2023.100124

Sun, Y., Li, S., & Yu, L. (2021). The dark sides of ai personal assistant: Effects of service failure on user continuance intention. *Electronic Markets*, *32*(1), 17–39. https://doi.org/10.1007/s12525-021-00483-2

Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of human–ai interaction (haii). *Journal of Computer-Mediated Communication*, *25*(1), 74–88. https://doi.org/10.1093/jcmc/zmz026

Süße, T., Kobert, M., & Kries, C. (2021). Antecedents of constructive human-ai collaboration: An exploration of human actors' key competencies. In L. Camarinha-Matos, X. Boucher, & H. Afsarmanesh (Eds.), *Smart and sustainable collaborative networks 4.0* (pp. 113–124). https://doi.org/10.1007/978-3-030-85969-5_10

Swift, T. (2016). The perilous leap between exploration and exploitation. *Strategic Management Journal*, *37*(8), 1688–1698. https://doi.org/10.1002/smj.2423

Tarafdar, M., Beath, C. M., & Ross, J. W. (2019). Using ai to enhance business operations. *MIT Sloan Management Review*, *60*(4), 37–44. https://sloanreview.mit.edu/article/using-ai-to-enhance-business-operations/

Tarafdar, M., & Gordon, S. R. (2007). Understanding the influence of information systems competencies on process innovation: A resource-based view. *The Journal of Strategic Information Systems*, *16*(4), 353–392. https://doi.org/10.1016/j.jsis.2007.09.001

Tarafdar, M., Page, X., & Marabelli, M. (2022). Algorithms as co-workers: Human algorithm role interactions in algorithmic work. *Information Systems Journal*, *33*(2), 232–267. https://doi.org/10.1111/isj.12389

Teodorescu, M., Morse, L., Awwad, Y., & Kane, G. (2021). Failures of fairness in automation require a deeper understanding of human-ml augmentation. *MIS Quarterly*, *45*(3), 1483–1500. https://doi.org/10.25300/misq/2021/16535

The Joint ACM/AIS IS2020 Task Force, Leidig, P., & Salmela, H. (2021). *A competency model for undergraduate programs in information systems*. Association for Computing Machinery.

Thiebes, S., Lins, S., & Sunyaev, A. (2020). Trustworthy artificial intelligence. *Electronic Markets*, *31*(2), 447–464. https://doi.org/10.1007/s12525-020-00441-4

Thong, J. Y. L., Hong, S.-J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies*, *64*(9), 799–810. https://doi.org/10.1016/j.ijhcs.2006.05.001

Tokadlı, G., Dorneich, M. C., & Matessa, M. (2021). Evaluation of playbook delegation approach in human-autonomy teaming for single pilot operations. *International Journal of Human–Computer Interaction*, *37*(7), 703–716. https://doi.org/10.1080/10447318.2021.1890485

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nat Med*, *25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

Toreini, P., Langner, M., Maedche, A., Morana, S., & Vogel, T. (2022). Designing attentive information dashboards. *Journal of the Association for Information Systems*, *22*(2), 521–552. https://doi.org/10.17705/1jais.00732

Torkzadeh, G., & Koufteros, X. (1993). Computer user training and attitudes: A study of business undergraduates. *Behaviour & Information Technology*, *12*(5), 284–292. https://doi.org/10.1080/01449299308924392

Toutaoui, J., Benlian, A., & Hess, T. (2022). Managing paradoxes in bi-modalvinformation technology functions: A multi-case study. *Information Systems Journal*, *32*(6), 1177–1202. https://doi.org/10.1111/isj.12396

Tschandl, P., Rinner, C., Apalla, Z., Argenziano, G., Codella, N., Halpern, A., Janda, M., Lallas, A., Longo, C., Malvehy, J., Paoli, J., Puig, S., Rosendahl, C., Soyer, H. P., Zalaudek, I., & Kittler, H. (2020). Human-computer collaboration for skin cancer recognition. *Nat Med*, *26*(8), 1229–1234. https://doi.org/10.1038/s41591-020-0942-0

Tully, S., Longoni, C., & Appel, G. (2023). Knowledge of artificial intelligence predicts lower ai receptivity. *PsyArXiv*. https://doi.org/10.31234/osf.io/t9u8g

Turing, A. M. (1950). I.—computing machinery and intelligence. *Mind*, *59*(236), 433–460. https://doi.org/10.1093/mind/lix.236.433

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. http://www.jstor.org/stable/1738360

Tyack, A., & Mekler, E. D. (2020). Self-determination theory in hci games research: Current uses and open questions. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3313831.3376723

Uptake Technologies Inc. (2023). Uptake product offering [Retrieved August 25, 2023]. https://www.uptake.com/products

van Giffen, B., Herhausen, D., & Fahse, T. (2022). Overcoming the pitfalls and perils of algorithms: A classification of machine learning biases and mitigation methods. *Journal of Business Research*, *144*, 93–106. https://doi.org/10.1016/j.jbusres.2022.01.076

Van Brummelen, J., Tabunshchyk, V., & Heng, T. (2021). "alexa, can i program you?": Student perceptions of conversational artificial intelligence before and after programming alexa. *Proceedings of the Interaction Design and Children*. https://doi.org/10.1145/3459990.3460730

Vanneste, B. S., & Puranam, P. (2024). Artificial intelligence, trust, and perceptions of agency. *Academy of Management Review*, *Forthcoming*. https://doi.org/10.5465/amr.2022.0041

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Proceedings of the 31st Conference on Neural Information Processing Systems*. https://papers.neurips.cc/paper/7181-attention-is-all-you-need.pdf

Vazhayil, A., Shetty, R., Bhavani, R. R., & Akshay, N. (2019). Focusing on teacher education to introduce ai in schools: Perspectives and illustrative findings. *Proceedings of the 2019 IEEE Tenth International Conference on Technology for Education (T4E)*. https://doi.org/10.1109/t4e.2019.00021

Verame, J. K. M., Costanza, E., Fischer, J., Crabtree, A., Ramchurn, S. D., Rodden, T., & Jennings, N. R. (2018). Learning from the veg box. *Proceeding of the 2018 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3173574.3174021

Vössing, M., Kühl, N., Lind, M., & Satzger, G. (2022). Designing transparency for effective human-ai collaboration. *Information Systems Frontiers*, *24*(3), 877–895. https://doi.org/10.1007/s10796-022-10284-3

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (ai) on firm performance: The business value of ai-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://doi.org/10.1108/bpmj-10-2019-0411

Wang, B., Rau, P.-L. P., & Yuan, T. (2022). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, *42*(9), 1324–1337. https://doi.org/10.1080/0144929x.2022.2072768

Wang, D., Yang, Q., Abdul, A., & Lim, B. Y. (2019). Designing theory-driven user-centric explainable ai. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300831

Wang, Q., & Shukla, P. (2013). Linking sources of consumer confusion to decision satisfaction: The role of choice goals. *Psychology & Marketing*, *30*(4), 295–304. https://doi.org/10.1002/mar.20606

Wang, Y., Skerry-Ryan, R., Stanton, D., Wu, Y., Weiss, R. J., Jaitly, N., Yang, Z., Xiao, Y., Chen, Z., Bengio, S., Le, Q., Agiomyrgiannakis, Y., Clark, R., & Saurous, R. A. (2017). Tacotron: Towards end-to-end speech synthesis. *Proceedings of the Interspeech 2017*. https://doi.org/10.48550/arXiv.1703.10135

Weber, M., Engert, M., Schaffer, N., Weking, J., & Krcmar, H. (2022). Organizational capabilities for ai implementation—coping with inscrutability and data dependency in ai. *Information Systems Frontiers*, *25*, 1549–1569. https://doi.org/10.1007/s10796-022-10297-y

Weber, P., Baum, L., & Pinski, M. (2023). Messung von ai literacy – empirische evidenz und implikationen. *Proceedings of the Wirtschaftsinformatik 2023*. https://aisel.aisnet.org/wi2023/3

Weber, P., Pinski, M., & Baum, L. (2023). Toward an objective measurement of ai literacy. *Proceedings of the Pacific Asia Conference on Information Systems 2023*. https://aisel.aisnet.org/pacis2023/60

Webster, J., & Watson, R. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*, *26*(2), 1195–1215. https://www.jstor.org/stable/4132319

Weinert, F. E. (2001). Concept of competence: A conceptual clarification. In D. S. Rychen & L. H. Salganik (Eds.), *Defining and selecting key competencies* (pp. 45–65). Hogrefe & Huber Publishers.

Wiebe, E. N., Lamb, A., Hardy, M., & Sharek, D. (2014). Measuring engagement in video game-based environments: Investigation of the user engagement scale. *Computers in Human Behavior*, *32*, 123–132. https://doi.org/10.1016/j.chb.2013.12.001

Wienrich, C., & Carolus, A. (2021). Development of an instrument to measure conceptualizations and competencies about conversational agents on the example of smart speakers. *Frontiers in Computer Science*, *3*. https://doi.org/10.3389/fcomp.2021.685277

Wiesche, M., Joseph, D., Thatcher, J., Gu, B., & Krcmar, H. (2020). It workforce. In *Mis quarterly research curations*. MIS Quarterly. http://misq.org/research-curations

Wiljer, D., & Hakim, Z. (2019). Developing an artificial intelligence-enabled health care practice: Rewiring health care professions for better care. *J Med Imaging Radiat Sci*, *50*(4 Suppl 2), S8–S14. https://doi.org/10.1016/j.jmir.2019.09.010

Willcocks, L. (2020). Robo-apocalypse cancelled? reframing the automation and future of work debate. *Journal of Information Technology*, *35*(4), 286–302. https://doi.org/10.1177/0268396220925830

Williams, C. (2021). Four reasons your ai plan is failing (and how to fix them) [Retrieved February 28, 2023]. https://www.ibm.com/blogs/think/uk-en/four-reasons-your-ai-plan-is-failing-and-how-to-fix-them/

Williams, M., Gharbi, H., Ulusan, A., Ergun, O., Xiaofeng, Z., Zhang, S., & Harteveld, C. (2016). Toward human in the loop optimization through game-based experiments. *Extended Abstracts of the 2016 Annual Symposium on Computer-Human Interaction in Play Companion*. https://doi.org/10.1145/2968120.2987733

Wilton, L., Ip, S., Sharma, M., & Fan, F. (2022). Where is the ai? ai literacy for educators. In M. Rodrigo, N. Matsuda, A. Cristea, & V. Dimitrova (Eds.), *Artificial intelligence in education. posters and late breaking results, workshops and tutorials, industry and innovation tracks, practitioners' and doctoral consortium* (pp. 180–188, Vol. 13356). https://doi.org/10.1007/978-3-031-11647-6_31

Wolff, A., Gooch, D., Cavero Montaner, J. J., Rashid, U., & Kortuem, G. (2016). Special issue on data literacy: Articles creating an understanding of data literacy for a data-driven society. *Journal of Community Informatics*, *12*(3), 9–26. https://doi.org/10.15353/joci.v12i3.3275

Wong, G. K. W., Ma, X., Dillenbourg, P., & Huan, J. (2020). Broadening artificial intelligence education in k-12. *ACM Inroads*, *11*(1), 20–29. https://doi.org/10.1145/3381884

World Economic Forum. (2018). *The future of jobs report* (Report). World Economic Forum. http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf

World Economic Forum. (2020). *Schools of the future. defining new models of education for the fourth industrial revolution.* (Report). World Economic Forum. http://www3.weforum.org/docs/WEF_Schools_of_the_Future_Report_2019.pdf

World Economic Forum. (2022a). *Empowering ai leadership: Ai c-suite toolkit* (Report). World Economic Forum. https://www.weforum.org/publications/empowering-ai-leadership-ai-c-suite-toolkit/

World Economic Forum. (2022b). Without universal ai literacy, ai will fail us [Retrieved August 10, 2022]. https://www.weforum.org/agenda/2022/03/without-universal-ai-literacy-ai-will-fail-us/

Xie, Y., Bodala, I., Ong, D. C., Hsu, D., & Soh, H. (2019). Robot capability and intention in trust-based decisions across tasks. *Proceedings of the 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. https://doi.org/10.1109/HRI.2019.8673084

Xu, J. J., & Babaian, T. (2021). Artificial intelligence in business curriculum: The pedagogy and learning outcomes. *The International Journal of Management Education*, *19*(3). https://doi.org/10.1016/j.ijme.2021.100550

Yang, J., Blount, Y., & Amrollahi, A. (2021). Factors that influence the adoption of artificial intelligence by auditing firms. *Proceedings of the Forty-Second International Conference on Information Systems*. https://aisel.aisnet.org/icis2021/is_implement/is_implement/5

Yang, W. (2022). Artificial intelligence education for young children: Why, what, and how in curriculum design and implementation. *Computers and Education: Artificial Intelligence*, *3*. https://doi.org/10.1016/j.caeai.2022.100061

Yaniv, I. (2011). Group diversity and decision quality: Amplification and attenuation of the framing effect. *International Journal of Forecasting*, *27*(1), 41–49. https://doi.org/10.1016/j.ijforecast.2010.05.009

Yeh, S.-F., Wu, M.-H., Chen, T.-Y., Lin, Y.-C., Chang, X., Chiang, Y.-H., & Chang, Y.-J. (2022). How to guide task-oriented chatbot users, and when: A mixed-methods study of combinations of chatbot guidance types and timings. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3501941

You, S., Yang, C. L., & Li, X. (2022). Algorithmic versus human advice: Does presenting prediction performance matter for algorithm appreciation? *Journal of Management Information Systems*, *39*(2), 336–365. https://doi.org/10.1080/07421222.2022.2063553

Yuan, C. W., Bi, N., Lin, Y.-F., & Tseng, Y.-H. (2023). Contextualizing user perceptions about biases for human-centered explainable artificial intelligence. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3544548.3580945

Yukl, G., & Fu, P. P. (1999). Determinants of delegation and consultation by managers. *Journal of Organizational Behavior*, *20*(2), 219–232. https://www.jstor.org/stable/3100422

Zhang, F., Wei, L., Yang, J., & Zhu, L. (2018). Roles of relationships between large shareholders and managers in radical innovation: A stewardship theory perspective. *Journal of Product Innovation Management*, *35*(1), 88–105. https://doi.org/10.1111/jpim.12376

Zhang, J., Adomavicius, G., Gupta, A., & Ketter, W. (2020). Consumption and performance: Understanding longitudinal dynamics of recommender systems via an agent-based simulation framework. *Information Systems Research*, *31*(1), 76–101. https://doi.org/10.1287/isre.2019.0876

Zhang, P. (2013). The affective response model: A theoretical framework of affective concepts and their relationships in the ict context. *MIS Quarterly*, *37*(1), 247–274. https://www.jstor.org/stable/43825945

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering baron and kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*(2), 197–206. https://doi.org/10.1086/651257

Zhou, X., Brummelen, J. V., & Lin, P. (2020). Designing ai learning experiences for k-12: Emerging works, future opportunities and a design framework. *arXiv preprint*. https://doi.org/10.48550/arXiv.2009.10228

Zhu, J., Villareale, J., Javvaji, N., Risi, S., Löwe, M., Weigelt, R., & Harteveld, C. (2021). Player-ai interaction: What neural network games reveal about ai as play. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445307