AiLingo – A Design Science Approach to Advancing Non-Expert Adults' AI Literacy

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Completed Research Paper

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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

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 et al., 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; Yang & Wibowo, 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, 2022). 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, et al., 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, et al., 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, et al., 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 et al., 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.

Conceptual Background

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., 2021). 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.

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 et al., 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 et al., 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.

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 (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).

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 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.

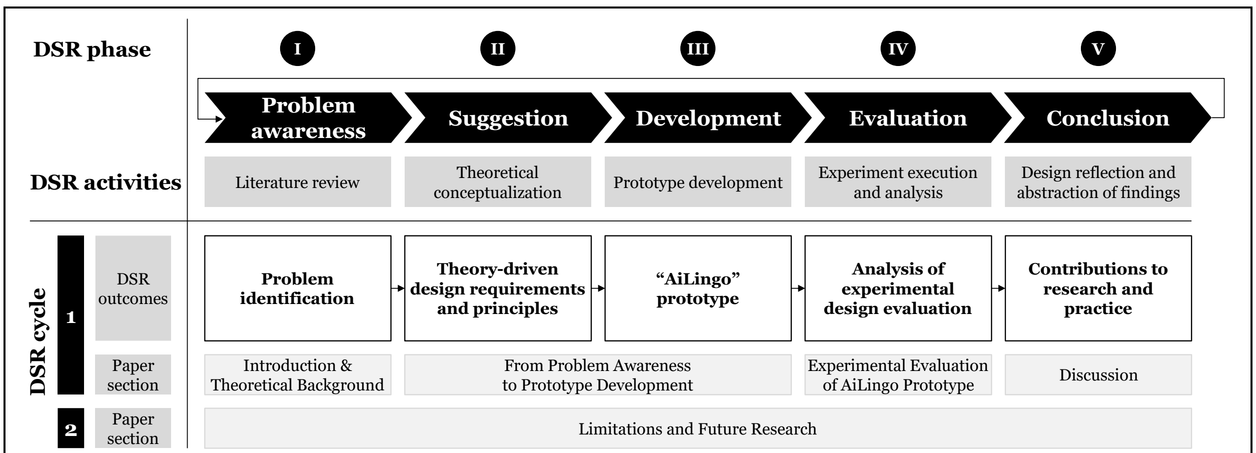


Figure 1. DSR Approach (adapted from Kuechler and Vaishnavi, 2012)

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

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 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 (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.

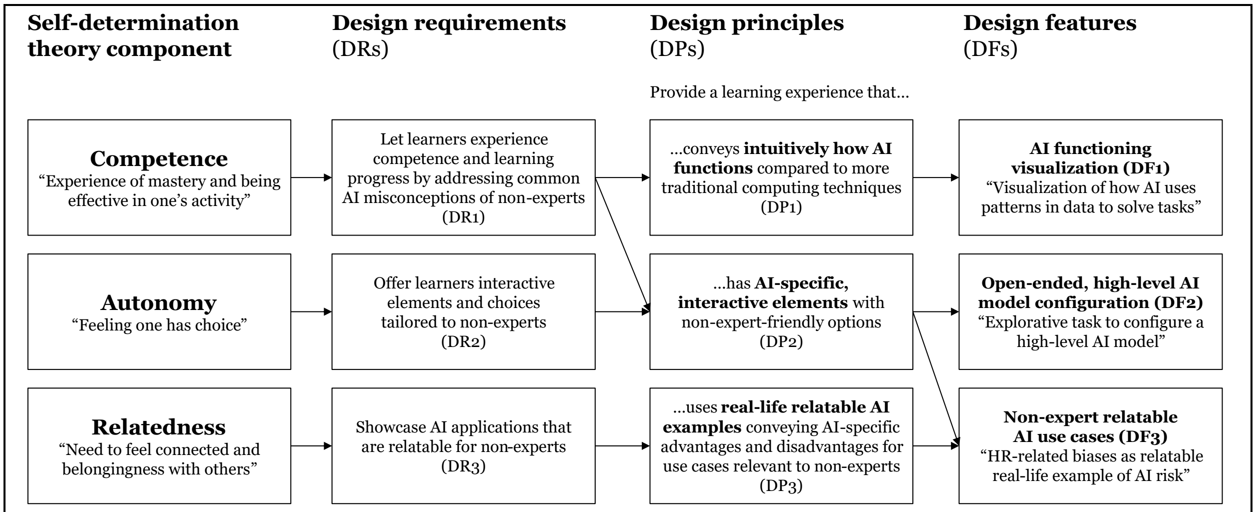


Figure 2. Design Requirements, Principles, and Features informed by SDT

Design Feature Instantiation (DSR Phase III)

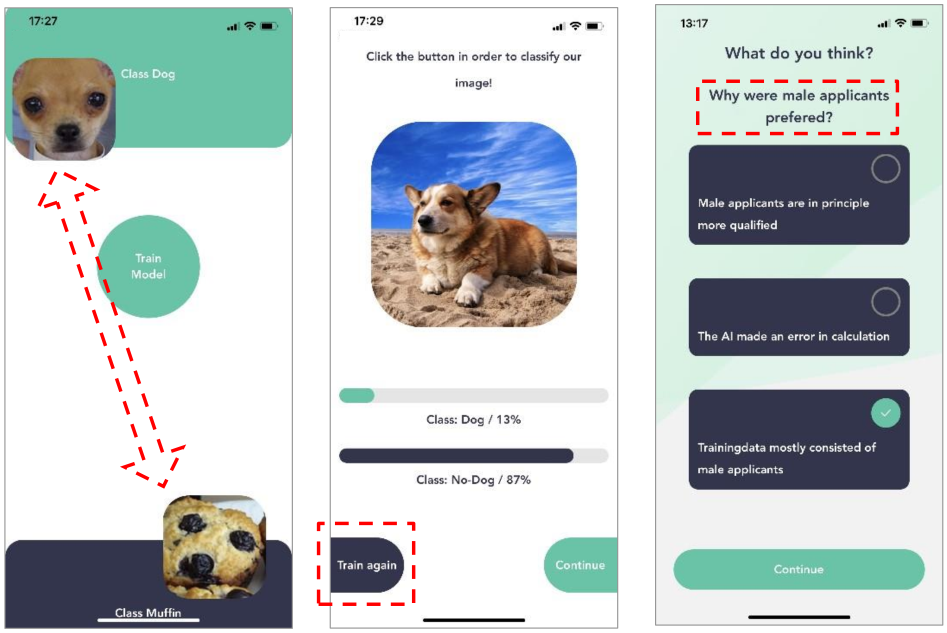
After the DP deduction, we instantiated each abstract DP as a specific DF of AiLingo, aiming to develop a learning app that adults can use easily. We developed and distributed (Android and iOS) AiLingo using Expo, an open-source framework that builds on React Native, enabling cross-platform development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



DF1: AI functioning visualization | **DF2: Open-ended, high-level AI model configuration** | **DF3: Non-expert relatable AI use cases**

Figure 3. Design Features from AiLingo Prototype

Experimental Evaluation of AiLingo Prototype (DSR Phase IV)

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 4.

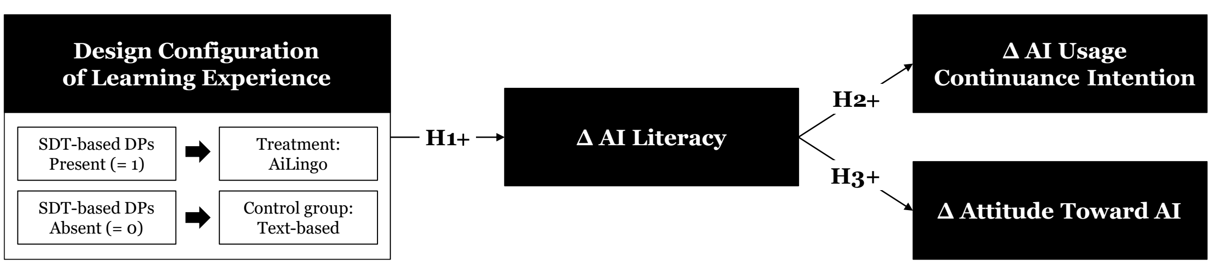


Figure 4. Research Model for Experimental Prototype Evaluation

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 (Yang & Wibowo, 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 et al., 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, Padiyath, et al., 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 et al., 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.*

Experimental Design

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.

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 (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 (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 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 Nomura et al. (2006). We made the scales AI-specific by replacing the representative term for "IS" and "robot" with the term AI (see Table 4). Table 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 0.8 (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.

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 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 2 and found that an SDT-based design configuration positively affects Δ AI literacy (β = 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 2 and found that Δ AI literacy positively affects Δ AI usage continuance intention (β = 0.062, 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 2 and found that Δ AI literacy also positively affects Δ attitude toward AI (β = 0.080, 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[D]	N/A[D]	1.10	N/A[D]		
	t2	7.95	2.52						
AI usage continuance intention[B] (ACI)	t1	5.78	1.17	0.93	0.91	1.07	0.42	**0.83**	
	t2	5.89	1.07						
Attitude toward AI[B] (ATA)	t1	3.84	1.13	0.82	0.81	1.10	-0.31	-0.56	**0.58**
	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 1. Descriptive Statistics and Correlations

DV (Model ID) / **Variable**	**Δ AI literacy** (1)		**Δ AI usage continuance intention** (2)		**Δ Attitude toward AI** (3)	
	β	*s.e.*	*β*	*s.e.*	*β*	*s.e.*
Intercept	0.157	0.845	-0.016	0.320	-0.088	0.313
Manipulation						
Design configuration[A]	**1.831*****	**0.432**				
Δ AI literacy			**0.062+**	**0.037**	**0.080***	**0.036**
Controls						
Age	0.028	0.021	0.006	0.009	0.007	0.008
Gender[B]	-0.632	0.459	-0.241	0.184	-0.346+	0.180
R^2	0.19		0.06		0.11	

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 < 0.1, * = p < 0.05, ** = p < 0.01, *** = p < 0.001

Table 2. Regression Results

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 (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 ($p < 0.001$) 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.

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 et al., 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 (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.

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.

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.

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Appendix

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. (2021) Pinski et al. (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)
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 et al. (2022)

Table 3. AI Literacy 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. Downstream Variable Measurement Items