AI & SOCIETY
https://doi.org/10.1007/s00146-025-02478-5

REVIEW

Measuring public opinion towards artificial intelligence: development and validation of a general AI attitude short scale

Marcus Novotny[1,2] · Wiebke Weber[1] · Christoph Kern[1,2] · Frauke Kreuter[1,2,3]

Received: 11 April 2025 / Accepted: 30 June 2025

Abstract
The rapid proliferation of artificial intelligence (AI) has sparked both enthusiasm and ethical concerns in societies. As AI continues to permeate daily life, policymakers need to understand how it is perceived by diverse stakeholders and communities. To reliably measure attitudes towards AI of the general public, a short scale is essential for universal application. Existing scales face limitations in applicability due to their length, sub-standard internal consistency, or a focus on only negative attitudes. In response, we built up on existing scales and developed a unidimensional six-item general AI attitude short scale. First tests on internet panel data from Germany ($n = 1001$) and the US ($n = 3091$) obtained favorable results for classical test theory (CTT) and item response theory (IRT). Confirmatory factor analysis indicated an excellent fit for a single-factor structure, while the scale also exhibited strong criterion-related validity, correlating positively with digital competency and predicting acceptance of several AI applications. Additional IRT analyses suggested high item discrimination, broad coverage of the attitude spectrum and no meaningful differential item functioning (DIF). Thus, we propose a psychometrically sound short scale for measuring general AI attitude and provide insights into the antecedents and consequences of the construct.

Keywords Artificial intelligence · Attitude measurement · Scale development · Survey research · Technology acceptance · AI risk

1 Introduction

Rapid advances in AI over the past decade have driven scientific breakthroughs, industry innovations, and everyday tools. Public interest surged after ChatGPT's release in November 2022, offering a clear, hands-on example of AI in action. The growing capabilities of AI have raised concerns about bias, privacy, and job displacement, prompting regulatory responses like the EU AI Act (Regulation (EU) 2024/1689) to safeguard fundamental rights. At the same time, governments around the world are exploring ways to harness AI to improve administrative efficiency and deliver public services more effectively (Fischer-Abaigar et al. 2024). As AI becomes more embedded in daily life, policymakers need timely, reliable data to understand public concerns and ensure governance balances innovation with the protection of rights and values (Livingston 2024; Montag et al. 2024). Ultimately, whether societies and their people will be able to use AI to their advantage will also depend on their attitudes towards it and acceptance of its applications (Montag and Ali 2025a).

Given the dynamic developments of AI technologies and its spread across domains, tracking public attitudes towards AI over time and in diverse contexts is critical to identify concerns of different subpopulations early on (Zhang 2023). Thus, prior research has called for an investigation of general attitudes towards AI in large representative samples around the world (Montag et al. 2024). Here, extensive multi-topic surveys such as the General Social Survey

✉ Marcus Novotny
marcus.novotny@stat.uni-muenchen.de

Wiebke Weber
wiebke.weber@stat.uni-muenchen.de

Christoph Kern
christoph.kern@stat.uni-muenchen.de

Frauke Kreuter
Frauke.Kreuter@stat.uni-muenchen.de

1 Ludwig-Maximilians-Universität München, Munich, Germany

2 Munich Center for Machine Learning (MCML), Munich, Germany

3 University of Maryland, College Park, Maryland, United States

(GSS) or the European Social Survey (ESS) are a natural fit, as they are regularly administered and have proven instrumental in informing public policy (Kolarz et al. 2022). However, to measure attitudes towards AI in such surveys, a reliable and valid short scale is needed. While a range of AI attitude scales have been proposed, several challenges limit their applicability. In particular, they tend to be too long (see Schepman and Rodway 2020, 2023), show substandard internal consistency (see Sindermann et al. 2021), focus only on negative aspects (see Wang and Wang 2022; Kieslich et al. 2022), or do not capture all three facets of attitudes—affective, behavioral, and cognitive (see Grassini 2023). Recently, Stein et al. (2024) proposed a single-factor instrument with twelve items that encompasses all facets, but may still be impractical for a single construct in large multi-topic surveys with rigid length limits. As an example, recent ESS questionnaires contain over 250 questions and should be administrable within 1 h, severely limiting the practical number of items per construct. Thus, the development of a concise yet robust scale is vital.

In response, we build upon prior work by Stein et al. (2024) to develop a general AI attitude short scale, adopting two items from each of the three attitude facets and adjusting the response scale to reduce cognitive strain and response biases (Saris et al. 2010). We tested the scale with two non-probability samples: an extensive survey of German internet users in August 2024 ($n = 1001$) and a shorter survey of US internet users in February 2025 ($n = 3091$). In doing so, we subjected the scale to a rigorous validation process grounded in both classical test theory (CTT) and item response theory (IRT; Hambleton and Jones 1993), which achieved favorable results.

Our contributions are twofold. First, we propose and validate a new general AI attitude short scale for large multi-topic surveys. Analyses from both CTT and IRT confirmed high psychometric quality, enabling usage in future studies for many different applications due to its generality. We are also the first study that analyzes an AI attitude scale using IRT, contributing to the integration of CTT and IRT approaches for a comprehensive approach to measurement (Embretson and Hershberger 1999). By incorporating items referencing all facets of attitudes (affective, behavioral and cognitive), we also offer the only conceptually holistic measurement instrument next to Stein et al. (2024). Due to the general nature of its items, we expect the scale to remain applicable even as AI technology evolves further. General applicability is important to track attitudes over time despite pending advances, such as the emergence of advanced chatbots or autonomous systems, without constantly revising the instrument.

Second, we provide empirical insights into current public sentiment towards AI across socio-demographic groups in Germany. Among our quota-based sample from a volunteer panel of internet users, we found that younger respondents and those with prior AI experience, higher education, and greater digital competency generally held more positive attitudes towards AI. On the contrary, older individuals and females tended to be more skeptical. We also studied the acceptance of AI-based systems across low-, medium- and high-risk contexts to establish criterion validity of our scale, using a measure of AI acceptance based on prior research by Koenig (2024). Our scale consistently predicted AI acceptance across all contexts, explaining a substantial portion of the variance. It also interacted as expected with established moderators from attitude research, with attitude strength (*extremity*) enhancing, and structural ambivalence (*cognitive–affective inconsistency*) weakening the predictive power of AI attitudes. Notably, the influence of additional socio-demographic predictors is context-dependent. For instance, digital competency and AI familiarity strongly predicted acceptance in low-risk contexts but showed no or even reversed effects in high-risk scenarios. These results underscore both the robust predictive utility of our scale and the nuanced, context-dependent nature of AI acceptance, highlighting how socio-demographic factors shape individuals' readiness to embrace AI.

2 Theoretical background

2.1 Conceptualizing artificial intelligence

The term AI is notoriously hard to define and has lacked a consistent definition in prior research (Goertzel and Achler 2014; Kelly et al. 2023). Broadly speaking, AI refers to systems capable of tasks that typically require human intelligence and are not following deterministic approaches, but learn relationships from data. AI can be generalized into 'weak' or 'strong' applications, also referred to as Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI). ANI systems are task-specific and already in widespread use today to support human behavior and decision-making (e.g., voice assistants, facial recognition, driving assistance; Maslej et al. 2024), whereas AGI systems would be able to generalize knowledge across domains and learn new tasks autonomously (Firt 2020; McLean et al. 2023).[1] While there are several AGI research projects, including OpenAI or Google's DeepMind (Baum 2017), the concept has not been realized yet. It has, however, been argued that the most advanced Large Language Models may

[1] Some authors also use the term Artificial Super Intelligence (ASI) to reference systems with capabilities above AGI and far beyond human intelligence (Gill 2016; Kelly et al. 2023), though the distinction is not quite clear (McLean et al. 2023).

resemble an early version of AGI and that AGI would have a major impact on our society (Bubeck et al. 2023).

The conceptualization of AI in public perception has evolved significantly over the years, shaped by advancements in technology and media narratives (Zhai et al. 2020; Nguyen and Hekman 2024). For technological advancements, a pivotal moment was the release of the Large Language Model ChatGPT by OpenAI in November 2022, which gathered wide attention as it made the concept of AI perceptible to many general citizens for the first time (Ryazanov et al. 2024). Following Zhai et al. (2020), media narratives often oscillate between utopian visions (e.g., AI as a tool for human enhancement) and dystopian concerns (e.g., job displacement and surveillance). This makes public attitudes towards AI relevant, as AI technologies are eventually placed in social contexts, where humans interact with algorithmic recommendations, decisions or AI-generated content. Phenomena such as under- or over-reliance on algorithmic outputs are shaped by this interplay and depend on individual attitudes towards and experiences with AI in a given context (Schenk and Kern 2024). Thus, the successful deployment of AI across society will also depend on public perceptions of such technologies, with studies finding stark differences for acceptance across use cases (Schepman and Rodway 2020; Kern et al. 2022; Livingston 2024).

2.2 The role of attitudes in behavioral and technology acceptance research

Since the late nineteenth century, research on attitudes has played a crucial role in the social sciences as a foundational concept for understanding human beliefs and behavior (Allport 1935). Attitudes can be defined as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (Eagly and Chaiken 1993, p. 1). As such, attitudes are expected to influence behavior and decision-making in various contexts, including consumer psychology (e.g., Asiegbu et al. 2012), political participation (e.g., Wang 2007), and interpersonal relationships (e.g., Byrne 1961). This has led to the development of several specialized attitude scales and their fielding in large-scale surveys such as the ESS (Jowell et al. 2007) or GSS (Smith et al. 2019) to track their nature and evolution across different populations. Attitudes can vary in several ways, including their valence (positive or negative orientation) or strength (durability and impact; Briñol et al. 2019). Attitude strength is especially complex and encompasses several properties. These include extremity (the degree of valence), perceived importance, level of certainty, extent of knowledge, and whether one's evaluation is consistent or ambivalent, i.e., holding both positive and negative views (Krosnick and Petty 1995; Howe and Krosnick 2017). Research has shown that strongly held attitudes are more enduring and powerful predictors of behavior (Krosnick and Petty 1995), while inconsistent or ambivalent attitudes have decreased predictive power (Conner et al. 2021). Thus, it is advisable to measure not only the valence of an attitude, but also strength-related measures. These may include whether a respondent is familiar with the topic, or has engaged in relevant behavior (Price 1992).

Following the tripartite model outlined by Rosenberg and Hovland (1960), attitudes also consist of three different classes of information, or facets: affective, behavioral and cognitive. The affective facet is typically regarded as the most important and refers to emotional responses or feelings associated with an attitude object. The behavioral facet represents behavioral intentions towards, while the cognitive facet encompasses beliefs and thoughts about the attitude object. There are differing views whether these facets resemble distinct attitude dimensions (multidimensional model; e.g., Breckler 1984), or whether they serve as inter-related indicators of a single underlying evaluative construct (unidimensional model; e.g., Eagly and Chaiken 1993). While the unidimensional model is most common in measurement practice, competing specifications—such as correlated or bifactor models—can be theoretically justified and empirically tested. Importantly, a single total score summed across items may still be meaningfully interpreted when multidimensionality is present, provided the general factor accounts for substantial shared variance among items (Reise et al. 2010).

Within attitudes research, the influence on behavior is a major research strand (Briñol et al. 2019). Attitudes are generally considered predictors of behavior, provided that both attitude and behavior are measured at a similar level of generality (Ajzen et al. 2018), and the attitude is strongly held (Krosnick and Petty 1995). To further explain behavior in specific contexts, theories such as the Theory of Planned Behavior (TPB; Ajzen 1985, 1991) were conceived, which posits that attitudes influence behavioral intentions, which in turn predict actual behavior. Several alternatives to the TPB were developed to better explain the attitude–behavior relationship in the context of technology usage (Marangunić and Granić 2015), with the most established ones being the Technology Acceptance Model (TAM; Davis 1986, 1989) and its extension, the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al. 2003). While the initial version of the TAM still contained a general attitude construct as mediating variable, it was later dropped, leaving the more concrete variables perceived usefulness and perceived ease of use as predictors of behavioral intention.

Although TAM and UTAUT are established frameworks for technology acceptance, AI is encountered in a wide spectrum of scenarios from deliberate usage to passive encounters, which poses novel challenges (Montag et al. 2024). As an example, individuals may not even have a chance to

Table 1 Overview of existing AI attitude scales

Scale	Factor structure	# Items	Scale	Test populations
Schepman and Rodway (2020, 2023)	2 factors *(positive, negative)*	20	5-point Agree–disagree Fully labeled	Originally UK; replications in Germany, Korea, Türkye (see Schepman and Rodway 2025)
Sindermann et al. (2021)	2 factors *(acceptance, fear)*	5	11-point Agree–disagree Endpoint labeled	Germany, China, UK
Grassini (2023)	1 factor	4	10-point Agreement Endpoint labeled	UK, US
Stein et al. (2024)	1 factor	12	5-point Agree–disagree Endpoint labeled	US, Germany

opt out of certain AI applications, such as algorithmic profiling models in government agencies (Kern et al. 2022). Thus, a more holistic model of the behavioral intention to engage with AI systems is needed, which can be termed AI acceptance (Kelly et al. 2023). Koenig (2024) has proposed such a model with three perspectives: user-centered technology acceptance, delegation (or automation) acceptance and societal adoption acceptance. User-centered technology acceptance follows the TAM logic, describing a person's willingness to intentionally use a technology, whereas delegation acceptance corresponds to a person's readiness to be subjected to an autonomous agent's actions. Finally, societal acceptance relates to one's acceptance of AI's application in society. These three perspectives detail different relations between people and AI, underlining the fact that AI is a general-purpose technology with a wide array of applications, which makes general attitudes towards it meaningful (Montag and Ali 2025a). This is especially true as acceptance of an AI system has been shown to vary largely across risk contexts, considering different aspects, such as performance, privacy or safety risks (Kelly et al. 2023; Ismatullaev and Kim 2024). As an example, citizens may generally approve of applications such as translating speech using AI, but less of AI acting as a medical doctor or therapist, while they may still hold an overall positive or negative attitude towards the technology (Schepman and Rodway 2020).

When trying to explain acceptance of AI systems, attitudes towards AI have repeatedly emerged as a significant predictor in reviews of the field (Kelly et al. 2023; Ismatullaev and Kim 2024). However, most of these studies rely on only slight extensions of the TAM, thus focusing more narrowly on user-centered technology acceptance, as well as the affective component of attitudes (e.g., Chen 2019; Man et al. 2020; Liang et al. 2020; Kim et al. 2020).

2.3 Existing AI attitude scales

Several general AI attitude scales have been proposed in prior research, including by Schepman and Rodway (2020, 2023), Sindermann et al. (2021), Grassini (2023), and Stein et al. (2024), see Table 1 for a chronologically sorted summary and Schepman and Rodway (2025) for a recent review.[2] Overall, both short and long scales have been proposed, with the number of items ranging from four to twenty, and AI attitude was either conceived as one overarching, or two opposing factors. Most studies developed agree–disagree scales with five or eleven response options, implying a natural midpoint or neutral option, whereas Grassini (2023) chose a unipolar agreement scale design. Finally, only two studies shared the introduction on AI provided to survey participants in their paper (see Schepman and Rodway 2020; Stein et al. 2024).

While all scales have been tested in multiple countries, none have been included in longitudinal cross-country evaluations. This may partly result from a lack of suitability for large, multi-topic survey panels, where shorter measures are required to avoid participant fatigue and attrition (Lee et al. 2004; Hoerger 2010). Especially Schepman and Rodway (2020), yet also Stein et al. (2024) are too large with 20 and 12 items, respectively. Sindermann et al. (2021) and Grassini (2023) did not share a definition of AI for future usage, which we see as necessary due to the ambiguous nature of the concept, nor did they explicitly develop items addressing all three facets of attitudes.[3] In addition, Sindermann et al. (2021) showed subpar internal reliability ($0.6 < \alpha < 0.74$). Overall, only the ATTARI-12 scale by Stein et al. (2024) explicitly considers all three facets of attitude scales (cognitive, affective, and behavioral). However, while it treats attitude as a unidimensional

[2] Similarly to Schepman and Rodway (2025), we exclude studies a) measuring attitudes towards AI in specific domains, such as the workplace (e.g., Park et al. 2024), b) solely focusing on negative appraisals of AI (e.g., Stein et al. 2019; Kieslich et al. 2021; Wang and Wang 2022) or c) lack scale validation, either reusing established items such as from the TAM (e.g., Man et al. 2020) or proposing ultra-short single- or two-item-measures unsuitable for factor analysis (e.g., Montag and Ali 2025b).

[3] In particular, Grassini (2023) does not seem to address the affective component, while Sindermann et al. (2021) lack the behavioral component, instead including items on societal acceptance ("Artificial intelligence will cause many job losses").

construct, as defining additional latent variables for the facets did not meaningfully improve model fit, it showed inferior fit without an item wording factor.

Conceptually, some scales adopt a bipolar measurement approach with one factor capturing attitudes along a positive–negative continuum, while others distinguish between two separate factors, reflecting a bivariate model. This indicates divergent theoretical perspectives on the structure of attitudes, which largely revolve around the operationalization of attitude ambivalence. Schepman and Rodway (2025) are strong advocates for a bivariate measurement model with two factors, as they argue that people may hold both positive and negative views of AI at the same time. While prior research does suggest that bivariate models work best when attitude evaluation is not truly reciprocal (Cacioppo and Berntson 1994), alternative measurement models for ambivalence in bipolar scales exist. As an example, the midpoint of a bipolar scale (McGrane 2019) or differences between cognitive and affective evaluations (Conner et al. 2021) can also represent such ambivalence or inconsistencies.

Finally, Grassini (2023), Schepman and Rodway (2023) and Stein et al. (2024) all established convergent and discriminant validity by analyzing correlations with related constructs, such as technology readiness. Sindermann et al. (2021) instead showed criterion validity through a correlation of their scale with items for willingness to use certain AI products. All studies also analyze the effects of demographic factors on AI attitude, yet find ambiguous results on their strength and direction. Age has been found to have a significant negative effect in some studies (Stein et al. 2024; Schepman & Rodway 2023), while others reported no significant relationship (Sindermann et al. 2021; Grassini 2023). Gender effects were similarly inconsistent: while Schepman & Rodway (2023), Grassini (2023) and Sindermann et al. (2021) found that female gender was associated with more negative AI attitude, Stein et al. (2024) reported no significant effect. Education has shown no significant relationship with AI attitude across two studies (Schepman and Rodway 2023; Grassini 2023), while computer expertise emerged as a strong positive predictor (Schepman and Rodway 2023). Both Schepman and Rodway (2023) and Stein et al. (2024) also explored the inter-relationships between AI attitude and psychological constructs, such as the *Big Five*, identifying significant correlations with different personality factors. Despite none of these studies relying on representative samples, such conflicting evidence highlights the need for further analyses of the antecedents of AI attitudes.

3 Measure development

In the following, we detail the development of our AI attitude scale, as well as an AI acceptance index to test criterion validity. Development of both instruments followed established guidelines (Menold and Bogner 2016; DeVellis and Thorpe 2021).

3.1 AI attitude scale

Our aim was to develop a concise general attitude scale suitable for universal application while capturing the three facets of attitudes—affective, behavioral, and cognitive (see Sect. 2.2). We thus conceptualize AI attitude as a reflective, unidimensional latent construct, where all items share a common underlying cause (DeVellis and Thorpe 2021). In this view, the three facets resemble inter-related expressions of the same evaluative disposition: someone with a strongly positive attitude towards AI will tend to like the idea of AI (affective), show willingness to use (behavioral) and hold favorable beliefs about it (cognitive). To construct the scale, we intended to create or adapt two items for each facet, resulting in a total of six items. This length was chosen as it aligns with other short scales (e.g., Keum 2021).

After careful review of existing measures, we drew six items from the single-factor scale by Stein et al. (2024), which already addressed the three attitudinal facets. From each facet, we adopted the two items which showed highest factor loadings and were not reverse-coded, as the original study reported item-wording effects and empirical evidence suggests that reverse-coded items can introduce method bias (Podsakoff et al. 2003). Furthermore, to allow for greater variance in responses, we modified the original five-point, endpoint labeled agree–disagree response scale to a seven-point, endpoint labeled scale, ranging from “Not at all” (“Gar nicht”) to “Definitely” (“Auf jeden Fall”). Longer response scales enable respondents to express more nuanced degrees of their attitudes and opinions, and typically exhibit better measurement quality (Saris and Gallhofer 2014). Given that survey respondents increasingly use mobile devices, we propose a seven-point scale, which is manageable on smaller screens, yet can be considered quasi-continuous for analysis. Regarding response categories, prior research has shown that agree–disagree scales reduce data quality compared to item-specific formats that simplify the response process, leading us to adopt the latter alternative (Saris et al. 2010; Dykema et al. 2022). The resulting six German survey items and their English translations are shown in Table 2.

Finally, we opted to provide participants with the definition of AI proposed by Stein et al. (2024) as an

Table 2 Items for AI attitude scale

Item	Facet	Full text—German (used in survey)	Full text—English translation
#1	Cognitive	Inwieweit sind Sie der Meinung, dass künstliche Intelligenz die Welt verbessern wird?	To what extent do you think artificial intelligence will make this world a better place?
#2	Behavioral	Wie sehr möchten Sie Technologien nutzen, die auf künstlicher Intelligenz basieren?	How much would you like to use technologies that rely on artificial intelligence?
#3	Affective	Wie sehr freuen Sie sich auf zukünftige Entwicklungen im Bereich künstliche Intelligenz?	To what extent do you look forward to future developments in the field of artificial intelligence?
#4	Cognitive	Inwieweit glauben Sie, dass künstliche Intelligenz Lösungen für globale Probleme bietet?	To what extent do you believe that artificial intelligence offers solutions to global problems?
#5	Affective	Haben Sie hauptsächlich positive Gefühle, wenn Sie an künstliche Intelligenz denken?	Do you have mostly[a] positive feelings when you think about artificial intelligence?
#6	Behavioral	Inwieweit würden Sie sich eher für eine Technologie mit künstlicher Intelligenz entscheiden als für eine ohne?	To what extent would you rather choose a technology with artificial intelligence than one without it?

Note: Item quality estimates are reported in Appendix A2

[a]The word "mostly" in item #5 has been accidentally fielded as "mainly" in our US sample. However, we do believe that this did not meaningfully impact results. The German sample is unaffected

introductory statement, as the term cannot be expected to be common knowledge yet and it is a common complaint that AI surveys do not offer definitions.[4] We favor this broad introduction as AI is evolving quickly and more concrete definitions would have to adapt often, whereas we seek to develop a scale which should maintain relevance for measurement over time. The introduction is reproduced in Appendix A1.

To evaluate the quality of our adaptations, we utilized the Survey Quality Predictor (SQP; Saris 2022). SQP is an open-access tool developed to estimate the quality of survey items in terms of their reliability and validity, using the formal and linguistic characteristics of the items. It was built on the idea of combining empirical quality estimates from multitrait–multimethod (MTMM) experiments with the specific characteristics of survey items. Based on this, a random forest algorithm predicts the quality estimates along with their corresponding prediction intervals and standard errors for newly added and coded items (Felderer et al. 2024). The manual coding follows the coding scheme developed by Saris and Gallhofer (2014), whereby 20 to 60 out of a total of 73 item characteristics have to be coded. Here, we coded the items of Stein et al. (2024) and compared their measurement quality to our newly adapted items. As presented in Appendix A2, all new items obtain a higher measurement quality.

[4] In their systematic review on AI acceptance, Kelly et al. (2023) found 38 of their 60 analyzed empirical studies did not define AI for study participants.

3.2 AI acceptance scenarios and index

To test criterion validity and the attitude–behavior relationship for our AI attitude scale, we also intended to measure AI acceptance. Existing measurement instruments were either fixated on specific application areas not fit for our German sample, such as US government policy (Livingston 2024), or focused only on user-centered technology acceptance as defined in TAM (e.g., Chen 2019). Thus, we developed a holistic instrument based on the framework by Koenig (2024), encompassing three application scenarios and a three-item index. All scenarios and items were discussed in detail in the author team to ensure content validity. We refer to this instrument as an index, as AI acceptance is a formative measure, with items sharing a common effect instead of a common cause (DeVellis and Thorpe 2021).

We measured AI acceptance for three different risk scenarios, given different types of risk emerged as repeated predictors of acceptance in prior reviews (Kelly et al. 2023; Ismatullaev and Kim 2024). We chose scenarios based on the study by Schepman and Rodway (2020), which had participants rate 42 AI applications on how comfortable they would feel with them. Results varied widely, with the authors suggesting that lower comfortableness ratings resulted from applications characterized by ethical dilemmas, a need for expert and social understanding, or limited suitability for automation. We grouped these considerations as *risk*, aiming to select three applications with strongly differing risk levels which are relatable to the general population. This led us to (1) translating speech (low risk; ~ 90% felt comfortable), (2) reviewing legal contracts (medium risk; ~ 66% felt comfortable) and (3) providing psychological counseling (high risk; 12% felt comfortable). To make scenarios comparable, we used a consistent structure in writing, shown in

Table 3 for the low-risk translation example. Each scenario explained the use case and its potential benefit to the user, before highlighting the actual contribution of AI and closing with the data source from which this ability is learned. All risk scenarios and their English translation can be found in Appendix A3.

To holistically measure AI acceptance per scenario, we developed three items building up on suggestions in Koenig's (2024) supplemental materials, introduced in Table 4. The items cover the three acceptance dimensions—user acceptance, delegation acceptance and societal acceptance. Again, all items were measured on a seven-point, endpoint-labeled scale in German language from "Not at all" ("Gar nicht") to "Definitely" ("Auf jeden Fall").

4 Data

We evaluated our measures using two samples from Germany and the US, as summarized in Table 5. As only the German sample included both the AI attitude scale and AI acceptance index with the three scenarios, it served as our primary data set and is introduced first.

The German sample was part of a broader survey study (forthcoming), which also contained questions about socio-demographic characteristics (e.g., *age*, *gender*, *education*, *employment, and household income*), *AI familiarity*, *digital competency* (Herklotz and Haensch 2025), *job satisfaction* (based on Fischer and Lück 1977), *job security* and *political orientation* (GESIS 2023), described in Appendix A4. The study recruited survey participants via the Bilendi Online Access Panel, consisting of volunteers from Germany who are reached through various online channels, such as search engine ads and social media. It used separate quotas for *age*, *education*, and *gender* to sample individuals with internet access aged 18 to 64 living in Germany, with reference distributions sourced from the German Microcensus (Destatis 2022). Participants first answered mandatory questions related to the quotas, which were utilized for screening and sampling purposes. Subsequently, they could skip any items they preferred not to answer. After indicating whether they had heard about AI before (*AI familiarity*), participants

Table 3 Composition of exemplary risk scenario (low-risk)

Scenario sentence—English translation	Purpose
Artificially intelligent systems can be used to translate text into other languages in real time. This can make it possible to communicate with other people whose language one does not speak	Introduction of use case and benefit to the user
Artificial intelligence is employed in this context to enable automatic translation at high speed	Actual contribution of artificial intelligence
The system learns this ability from a large data set of examples of existing translations (e.g., books published in German and English)	Training data source from which ability is learned

Table 4 Items for AI acceptance index

Item	Dimension	Full text—German (used in survey)	Full text—English translation
#1	User acceptance	Inwieweit würden Sie das vorgestellte System benutzen?	To what extent would you use the presented system?
#2	Delegation acceptance	Wie sehr wären Sie bereit, die vorgestellte Aufgabe vollständig dem System zu überlassen?	To what extent would you be willing to leave the presented task completely to the system?
#3	Societal acceptance	Inwieweit stimmen Sie zu, dass so ein System in unserer Gesellschaft genutzt werden sollte?	To what extent do you agree that such a system should be used in our society?

Table 5 Data sets analyzed in the study

	Sample 1—Germany	Sample 2—US
Reference distribution	German residents with internet access aged 18 to 64 according to Microcensus	US residents from age 18 on, according to 2021 Census
Sampling	Internet sample from Bilendi; separate quotas for age, education, gender	Internet sample from Prolific; joined quotas for age, ethnicity, gender
Final sample size	$n = 1001$	$n = 3091$
Collection period	August 7–16, 2024	February 20–28, 2025
Included measures	AI attitude, AI acceptance	AI attitude

then directly proceeded to our measures on AI attitude and acceptance, before completing the rest of the study.

The German data were collected between August 7 and August 16, 2024. A total of 17226 individuals were invited to participate in the survey, of which 1718 did. Several groups of participants were excluded to ensure data quality and alignment with the study design: first, 402 were screened out due to being outside the eligible age range (under 18 or over 64) or residing outside of Germany. Second, 230 respondents were excluded, because their demographic quota groups were already filled. Third, 32 respondents dropped out mid-survey, leaving 1054 who completed it. Fourth, after inspecting the distribution of survey completion times, we excluded the fastest 3% of respondents ($n = 31$) to remove potential speeders.[5] Finally, 22 participants who did not answer all survey items of our AI attitude and acceptance measures were excluded, resulting in a final sample of $n = 1001$.

We also fielded the AI attitude scale in a second US multi-topic survey. As the survey was designed for another forthcoming experimental study, it contained only few socio-demographics or constructs relevant to our research. We thus only used this data to study the distribution and factorial structure of our AI attitude scale. US survey participants were recruited via the Prolific Panel, which is popular for AI research and data annotation tasks and consists of volunteers mostly recruited via word of mouth and social media. The study used joined quotas (cross-stratification) for age, gender and ethnicity to approximate reference distributions from the 2021 US census (U. S. Census Bureau 2023). All respondents were required to be US residents. Participants were first asked whether they had heard about AI before (*AI familiarity*), followed immediately by our AI attitude scale, before completing the remaining survey. All questions were required to answer. 3187 participants completed the survey between February 20 and February 28, 2025. After inspecting the distribution of page-level completion times for our scale, we again excluded the fastest 3% of respondents ($n = 96$) to remove speeders. This resulted in a final sample of $n = 3091$.

Power analysis with the R package semPower (version 2.1.1; Moshagen and Bader 2024) determined a minimum required sample size of 697 participants for a single-factor model with six items (Type-I error $\alpha < 0.05$, desired $\beta = 0.20$, power = 0.80, RMSEA < 0.05), which both samples exceeded. Participation in both surveys was compensated, voluntary, and could be aborted at any time. All participants remained anonymous to the authors.

5 Statistical analyses and scale evaluation

Analyses were conducted in four phases using the statistical software R (version 4.4.3), following recommendations by DeVellis and Thorpe (2021). The code is publicly available, and we refer interested readers to the data availability statement. The first three phases were conducted using both samples: after (1) studying descriptive statistics and internal reliability of the scale, we (2) investigated factorial validity through confirmatory factor analysis and (3) applied IRT to evaluate item discrimination, difficulty, and differential item functioning (DIF). Finally, we (4) conducted multiple linear regression analyses on our German sample to examine the relationships between AI attitude and demographic variables, and to establish criterion validity by testing our AI attitude scale as a predictor of AI acceptance. As we conceptualized AI acceptance as a formative measure, we excluded it from our analyses of internal reliability, factor structure and IRT.

5.1 Descriptive statistics and internal reliability

First, descriptive measures for individual items and summary scores of our proposed AI attitude scale and AI acceptance index were calculated. We also examined skewness and kurtosis and inspected histograms of the mean scores for both measures to evaluate their distributions. Internal reliability of the AI attitude scale was assessed using Cronbach's alpha (α; Cronbach 1951; Morera and Stokes 2016).

5.2 Confirmatory factor analysis

Based on Stein et al. (2024), a single-factor structure was hypothesized for our shortened attitude scale, which we investigated through confirmatory factor analysis (CFA) in both samples.[6] Next to this unidimensional model (a), we also specified and tested two additional models to compare fit and inspect factor loadings: a correlated three-factor model (b), where items load on distinct but correlated factors for their respective facet, and a bifactor-S1 model (c), where an orthogonal cognitive and affective facet factor are defined next to the general attitude factor.[7]

[5] Completion times were only available for the full German survey, leading us to conduct our speeding analysis on the respondent level, instead of the preferable page-level (see Greszki et al. 2014). 31 respondents were not considered for the speeding analysis and retained, as no completion duration was known due to them answering and submitting the survey with interruptions.

[6] As a robustness check, we also conducted exploratory factor analysis (EFA) to confirm that a single factor structure would actually show best fit, which is reported in Appendix A5.

[7] No factor was defined for the behavioral facet, which acted as as a reference category (see Eid et al. 2017; Stein et al. 2024).

Model fit was evaluated using multiple fit indices and established benchmarks (see Schermelleh-Engel et al. 2003): comparative fit index (CFI, > 0.97 excellent fit, > 0.95 acceptable fit), standardized root mean squared residual (SRMR, < 0.05 for good fit, < 0.1 for acceptable fit) and root mean square error of approximation (RMSEA, < 0.05 for good fit, < 0.08 for adequate fit). All models were estimated using the *lavaan* R package (version 0.6–18; Rosseel 2012), with maximum likelihood estimation, constraining latent factor variances to 1. To enhance robustness, we followed Wolf and McNeish (2023) and computed dynamic fit index (DFI) cutoffs using the *dynamic* R package (version 1.1.0) for our unidimensional model (a). Unlike fixed fit thresholds, which may not generalize well across different samples and model specifications, DFI cutoffs are estimated using Monte Carlo simulations. The resulting cutoff levels 1 (*close fit*), 2 (*fair fit*), and 3 (*mediocre fit*) thus enable a nuanced assessment of fit quality.

5.3 Item response theory analyses

To ensure that scale items provide broad coverage of our latent trait (AI attitude, or "theta" θ) and perform consistently across demographic groups, we conducted IRT analyses on both our samples. We used a unidimensional Graded Response Model (GRM; Samejima 1968) with R package *mirt* (version 1.44; Chalmers 2012). Assessing the validity of the assumed IRT model, we followed recommendations by Reeve et al. (2007) and tested for its three fundamental assumptions: unidimensionality, local independence and item monotonicity. We assessed unidimensionality through GRM model fit and local independence through Yen's (1984) Q3 statistic, with values below 0.2 suggesting independence. Item monotonicity was examined through Mokken scale analysis (*mokken* R package, version 3.1.2; Andries Van Der Ark 2007).

For the GRM, we report the estimated discrimination (a) and difficulty parameters (b) for each item, which are defined on the same scale as the studied latent trait. Item discrimination indicates how effectively an item distinguishes between respondents with differing levels of AI attitude. In turn, difficulty parameters represent the latent trait thresholds required for respondents to have a 50% probability of selecting a specific or higher response category. Discrimination parameter estimates exceeding 1.7 signal very high differentiation, while widely distributed difficulty parameter estimates indicate measurement capabilities across a broad spectrum of the latent trait (Baker and Kim 2017). We again report common fit measures for our GRM, such as RMSEA, SRMSR and CFI, where the same thresholds from CFA hold (Schermelleh-Engel et al. 2003), as well as item-level RMSEA, plus marginal and empirical reliability (Zein and Akhtar 2024). Supporting our analysis with visual inspection, we studied test and item information curves, which illustrate measurement precision across various levels of the latent trait.

Finally, item-parameter invariance was evaluated to assess whether our scale measured AI attitude consistently across demographic groups. We tested for DIF by fitting multiple-group GRMs for the variables *gender* and *age*,[8] following the two-stage *MaxA1* approach described by Meade and Wright (2012). In the first stage, item parameters were constrained to be equal across groups and a likelihood ratio test was used to analyze whether freeing parameters for individual items significantly improved model fit, which would suggest DIF. From the non-significant items, we identified a candidate anchor item and refitted a model, where only its item parameters were constrained across groups. We then tested whether constraining other items would significantly worsen model fit (see also Thissen et al. 1993). As suggested by Meade (2010), we report STDS (summed average distance in expected scale scores across all six items), UETSDS and ETSSD (which can be interpreted like Cohen's d; Cohen 1988) as effect size measures for DIF from the second stage.

5.4 Regression analyses

Finally, we conducted multiple linear regressions on our German data to analyze the relationships between AI attitude, AI acceptance and other measures, thus also testing for criterion validity. We estimated six primary models: in models 1) to 3), AI attitude mean scores served as the dependent variable, with the following predictors added sequentially: (1) a set of common demographics (*age*, *education*, *female gender*) and *AI familiarity*; (2) *digital competency* (Herklotz and Haensch 2025), akin to computer expertise and previously identified as a strong positive predictor (Schepman and Rodway 2023); and (3) the remaining measures *employment*, *household income*, *job satisfaction*, *job security*, as well as *political orientation*. Next, models 4) to 6) utilized AI acceptance mean scores in our three risk contexts (low, medium and high) as target variables, to evaluate predictive power and criterion validity of our AI attitude scale. Next to AI attitude mean scores, these models contained the same predictors as model 2).

For all models, we report unstandardized regression coefficient estimates, robust standard errors (HC3) and goodness of fit (R^2 and RMSEA). As a robustness check, we conducted regression analyses with AI attitude factor scores derived from CFA instead of mean scores, reported in the

[8] We used *age* groups 18–39 and 40+ for testing, as effect sizes were only estimable between two groups in the *mirt* R package. Different age groups did not lead to meaningfully different test results or effect sizes.

Table 6 Descriptive statistics for AI attitude and acceptance mean scores. All measures use a 1–7 rating

Sample	Scale		Mean	SD	Skew	Kurtosis	Cronbach's α
Germany	AI attitude		3.77	1.58	−0.13	−0.65	0.95
	AI acceptance	Low risk	4.52	1.75	−0.55	−0.55	/
		Medium risk	4.15	1.75	−0.32	−0.74	/
		High risk	3.42	1.80	0.15	−1.01	/
US	AI attitude		4.48	1.48	−0.45	−0.42	0.95

Table 7 Goodness of fit for confirmatory factor analysis of our AI attitude scale

Sample	Model	χ2	df	CFI	RMSEA	SRMR	AIC	BIC
Germany	(a) Unidimensional	34.280	9	0.991	0.074	0.015	18,324	18,383
	(b) Correlated facets	9.675	6	0.999	0.033	0.006	18,281	18,355
	(c) Bi-factor S1	10.830	5	0.997	0.056	0.008	18,295	18,373
US	(a) Unidimensional	91.507	9	0.993	0.068	0.011	52,937	53,009
	(b) Correlated facets	63.914	6	0.995	0.07	0.008	52,897	52,988
	(c) Bi-factor S1	48.736	5	0.995	0.079	0.009	52,909	53,005

Appendix (A10, A11) with standardized regression coefficients. Regression assumptions were assessed through visual inspection of residual plots and formal tests for autocorrelation, homoscedasticity and normality of residuals, plus checks for collinearity and influential outliers.

Finally, we defined extended model specifications for models 4) to 6) to analyze two possible moderators of the relationship between AI attitudes and AI acceptance: attitude strength and structural ambivalence. Attitude strength was operationalized as *extremity*, the absolute distance of the mean AI attitude score from the midpoint per respondent, and ranged between 0 and 3. Structural ambivalence was operationalized as *cognitive–affective (C–A) inconsistency*, the absolute maximum score difference between any cognitive and affective item per respondent (see Conner et al. 2021), and ranged between 0 and 6.[9] For simplicity, we directly report these results with standardized coefficients and AI attitude factor scores from CFA in Appendix A12.

6 Results

6.1 Descriptive statistics and internal reliability

Table 6 shows descriptive statistics for our AI attitude and acceptance measures. Cronbach's alpha $\alpha = 0.95$ signaled excellent reliability of our AI attitude scale in terms of internal consistency across samples. The AI attitude mean score distribution approximated a normal distribution, with skewness and kurtosis in acceptable boundaries for psychometric instruments.

We also report descriptive statistics for all developed items, as well as socio-demographics and other collected measures in Appendix A6, including a correlation matrix. Histograms for both measures can be found in Appendix A7. Studying the distribution of AI attitudes, we see a floor effect in our German sample: 101 respondents (10% of the sample) selected the lowest agreement response (1) on all items. Notably, half of these respondents ($n = 51$) did not report prior knowledge of AI, suggesting the effect may be largely concentrated to this sub-group. The floor effect was not present in our US sample, where the AI attitude mean was substantially higher (4.48 vs. 3.77) and over 99% of respondents reported knowledge of AI.

6.2 Confirmatory factor analysis

Next, we report the CFA results for our unidimensional model (a), and two multi-dimensional models, correlated facets (b) and bifactor S-1 (c).[10]

Table 7 presents the goodness-of-fit indices, supporting construct validity. Fit measures met recommended

[9] We chose C-A inconsistency as our measure of structural ambivalence, as it covers a broader range of cognitive and affective evaluations compared to C-A ambivalence (Conner et al. 2021). An example would be simultaneously having a positive affective, and a negative cognitive evaluation: e.g., being excited about technological developments, but concerned about societal implications of AI.

[10] The bifactor S-1 model produced a warning regarding the variance–covariance matrix of estimated parameters, with the smallest eigenvalue marginally below zero (German Sample: -1.15e-05; US Sample: -3.48e-07). This is not uncommon in models with only two items per factor, and does not necessarily reflect misspecification. Given the small deviation, absence of convergence problems, and stability of parameter estimates, we see this as a numerical artifact rather than a substantive concern.

Table 8 Factor loadings for AI attitude scale—(a) unidimensional model, German sample

Item	Unstandardized estimates				Standardized estimates	
	Loading on general factor (Std. error)	95% CI Lower	95% CI Upper	Residual variance	Loading on general factor	Residual variance
#1	1.51 (0.04)	1.44	1.59	0.70	0.87	0.23
#2	1.62 (0.04)	1.55	1.70	0.66	0.89	0.20
#3	1.67 (0.03)	1.61	1.74	0.61	0.91	0.18
#4	1.40 (0.04)	1.31	1.49	1.19	0.79	0.38
#5	1.51 (0.04)	1.43	1.58	0.76	0.87	0.25
#6	1.53 (0.04)	1.45	1.60	0.65	0.88	0.22

Table 9 Standardized factor loadings for our AI attitude scale, German sample, and alternative model specifications: (b) correlated facets, (c) bifactor S-1 model

Item	(b) Correlated facets				(c) Bifactor S-1			
sfgfg	Affective	Behavioral	Cognitive	Residual variance	General Factor	Affective	Cognitive	Residu-alvari-ance
#1			0.91	0.17	0.87		0.19	0.22
#2		0.91		0.18	0.90			0.19
#3	0.91			0.18	0.91	-0.02		0.17
#4			0.81	0.34	0.77		0.36	0.27
#5	0.87			0.25	0.87	0.21		0.20
#6		0.89		0.20	0.89			0.22

thresholds (Schermelleh-Engel et al. 2003) across all specifications and both samples (CFI > 0.97 for excellent fit; SRMR < 0.05 for good fit; RMSEA < 0.08 for adequate fit). While model fit improved across most indices for the less restrictive models (b) and (c), fit for our unidimensional model was already very good, leaving little room to favor the more complex multidimensional specifications instead. This was also supported by an analysis of factor loadings (see further below).

Following Wolf and McNeish (2023), we also generate stricter DFI cutoffs tailored to our data for the unidimensional model. In our US sample, it met all of the highest *Level 1 (L1)* thresholds, while only narrowly missing *L1* but achieving all *Level 2 (L2)* thresholds in the German sample, thus indicating fair to close fit.[11] Finally, an inspection of modification indices for the unidimensional model in our German sample (*not shown in table*) revealed only small absolute standardized expected parameter changes ranging from 0.04 to 0.23 in our German sample (US sample: 0.04–0.15).

To further analyze factorial structure, we also inspected factor loadings. Table 8 shows factor loadings for the unidimensional (a) AI attitude scale in our German sample, with standardized loadings ranging from 0.79 to 0.91. Table 9 shows standardized factor loadings for alternative model specifications (b) and (c) in our German sample. In addition, in the bifactor S-1 (c) specification, all items loaded most strongly on the general factor. As the general attitude factor accounted for the majority of explained common variance, AI attitude is likely not a statistical artifact but a meaningful latent construct. This was supported by the fact that even in the correlated facets model (b), correlations between facets were very strong (between 0.93 and 0.99; not shown in table), implying they likely do not represent distinct constructs. Results for our US sample were not meaningfully different—replications of Table 8 and Table 9 are reported in Appendix A8.

6.3 Item response theory analyses

GRM analysis for our German sample is reported in Table 10. All items showed high discrimination (> 2.5) and difficulty parameters were distributed between −1.1 and + 1.5. Model fit was excellent for SRMSR = 0.038 and CFI = 0.993, with RMSEA only showing an adequate value of 0.082, but RMSEA values at or below 0.02 for all individual items. We found high empirical and marginal reliability (both 0.94). Evidence also supported all key IRT assumptions: unidimensionality was supported by CFA and GRM model fit, local independence by Yen's (1984) Q3 (all

[11] DFI thresholds: Germany, L1 | CFI: 0.993; RMSEA: 0.069; SRMR: 0.013; L2 | CFI: 0.982; RMSEA: 0.108; SRMR: 0.019;
US Sample, L1 | CFI: 0.991; RMSEA: 0.079; SRMR: 0.016; L2 | CFI: 0.982; RMSEA: 0.112; SRMR: 0.020.

Table 10 Graded response model (GRM) for AI attitude, German sample

Item	Discrimination	Difficulty thresholds T1	T2	T3	T4	T5	T6
#1	3.924	−1.091	−0.678	−0.266	0.432	1.057	1.545
#2	4.545	−1.050	−0.660	−0.253	0.322	0.902	1.336
#3	4.952	−0.969	−0.590	−0.217	0.379	0.860	1.325
#4	2.771	−1.098	−0.736	−0.243	0.481	1.106	1.587
#5	3.887	−0.963	−0.537	−0.067	0.577	1.124	1.600
#6	4.275	−1.020	−0.680	−0.252	0.486	1.032	1.534

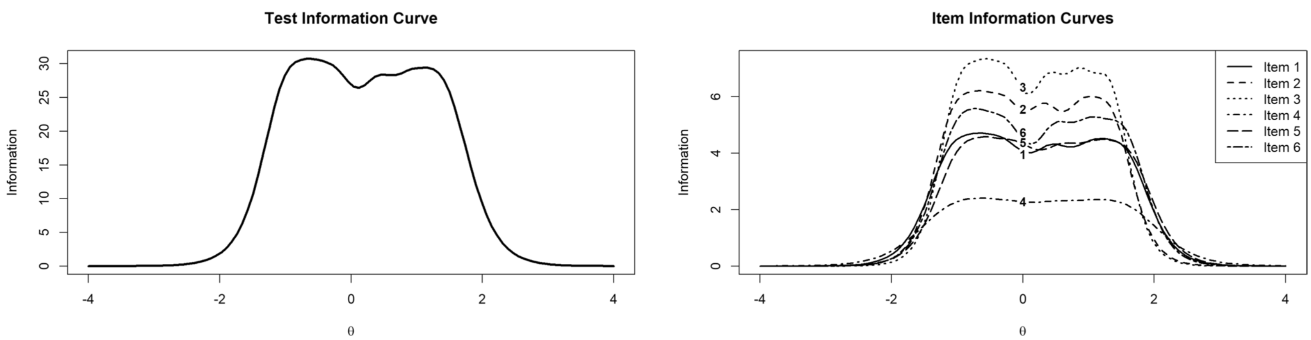

Fig. 1 Test (left) and item information curves (right) for AI attitude in our German sample

values < 0.08), and Mokken scale analysis showed no significant deviations from monotonicity (ItemH > 0.70; Crit = 0). Results in the US sample were similar, with again excellent model fit and even wider coverage for the lower end of the latent trait spectrum (difficulty parameters distributed between −2.0 and + 1.5). All US parameter estimates and fit indices are reported in Appendix A9.

Figure 1 presents the test and item information curves for our German sample. As the curve peaks around theta θ = 0, the scale was most precise for individuals with average levels of the latent trait. At values θ < −2 and θ > +2 test information dropped to near zero, suggesting limited reliability at measuring extreme attitudes, but good reliability for general population samples.[12] Analyzing item information curves, we see items showed redundancy (measuring the same range) and that all items provided sufficient information, with only item 6 contributing substantially less than other items, indicating higher standard error in measuring the latent trait. Again, US results were similar, apart from wider coverage and higher standard error for item 4. The respective figure for the US sample is provided in Appendix A9.

DIF analyses revealed no substantive concerns. Likelihood ratio tests in our German sample indicated only one significant difference each for grouping variables *gender* (item 4, $p < 0.05$) and *age* (item 6, $p < 0.01$), using item 3 as an anchor. However, both grouping variables showed low effect sizes ($STDS_{gender} = 0.062$, $UETSDS_{gender} = 0.124$, $ETSSD_{gender} = 0.007$; $STDS_{age} = 0.159$, $UETSDS_{age} = 0.180$, $ETSSD_{age} = 0.017$), with results for ETSSD well below Cohen's (1988) "small" threshold of 0.2. While tests in our US sample showed significant DIF for several more items for both gender (items 2, 3, 4) and age (all but item 4), effect sizes were again low ($STDS_{gender} = -0.542$, $UETSDS_{gender} = 0.546$, $ETSSD_{gender} = -0.063$; $STDS_{age} = 0.231$, $UETSDS_{age} = 0.273$, $ETSSD_{age} = 0.027$), suggesting that these differences are not practically meaningful. Significance levels were likely also inflated by our large sample size (Meade 2010), especially for US data. Plots of expected scores across subgroups also showed only minor differences for the US sample, and are presented in Appendix A9.

6.4 Regression analyses

Next, we proceeded with regression analyses to assess criterion validity. For all models we reported robust standard errors (HC3) to account for heteroscedasticity.

Table 11 shows the results from a hierarchical regression of AI attitude mean scores on our German data, sequentially introducing new predictors. Overall, models explained a modest share of variance in AI attitude ($R^2 = 20–25\%$). In

[12] Roughly 95% of the population would be expected to fall within −2 and + 2 in a standard normal distribution.

Table 11 Regression results for AI attitude, German data. Unstandardized regression coefficients, with robust standard error in parentheses

Target variable	AI attitude—mean total scores		
Model	(1)	(2)	(3)
(Intercept)	3.096***	2.285***	1.566**
	(0.257)	(0.291)	(0.546)
Age	−0.016***	−0.016***	−0.019***
	(0.003)	(0.003)	(0.004)
AI familiarity	1.018***	0.821***	0.772***
	(0.129)	(0.134)	(0.197)
Education	0.292***	0.207***	0.129*
	(0.050)	(0.053)	(0.066)
Female gender	−0.555***	−0.514***	−0.614***
	(0.090)	(0.089)	(0.109)
Digital competency		0.306***	0.353***
		(0.062)	(0.085)
Employment			−0.049
			(0.095)
Household income			0.010
			(0.046)
Job satisfaction			0.026
			(0.080)
Job security			0.250*
			(0.117)
Political orientation			0.049 +
			(0.030)
Num.Obs.	999	999	675
R^2	0.590	0.223	0.247
R^2 Adj	0.198	0.219	0.235
RMSE	1.42	1.39	1.35

Decreasing sample sizes are due to missing observations for job-related variables

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

model 1), all predictors were highly significant at $p < 0.001$. *AI familiarity* had the largest absolute positive influence on AI attitude ($B = 1.018$), followed by levels of *education* ($B = 0.292$). In comparison, being *female* had a strong negative impact on AI attitude (B = −0.555), while each year of *age* had a low negative impact ($B = -0.016$). Adding digital competency in model 2), we found a highly significant and positive effect ($B = 0.306$, $p < 0.001$), though R^2 increased only by about two absolute percentage points. Finally, additional variables in model 3) showed mostly insignificant results (*employment*, *household income*, *job satisfaction*). Notably, *job security* had a positive and significant effect on AI attitude ($B = 0.250$, $p < 0.05$) and we also found a small positive, barely significant effect for *political orientation* ($B = 0.049$, $p < 0.1$). This indicates that people who feel secure about maintaining their job and who indicated more right-wing political views expressed more positive attitudes towards AI. However, R^2 increased only by further 2% for this model. As a robustness check, we ran analyses also with our AI attitude factor derived from CFA as the target variable, showing no meaningfully different results, reported along with standardized regression coefficients (β) in Appendix A10.

Table 12 shows the regression results for AI acceptance from 4) low-, over 5) medium- to 6) high-risk contexts on our German data, using AI attitude mean scores as a predictor. Here, models explained a large share of variance in AI acceptance ($R^2 = 48–59\%$). Noticeably, R^2 was highest for low-risk contexts and decreased with increasing risk level. AI attitude was the strongest predictor and highly significant across models ($B > 0.75$, $p < 0.001$). Demographic variables exhibited varying effects across risk conditions. *Age* was positively associated with AI acceptance in low-risk contexts ($B = 0.010$, $p < 0.001$) but negatively associated in high-risk

Table 12 Regression results for AI acceptance across risk contexts, German data. Unstandardized regression coefficients, with robust standard error in parentheses

Target variable	AI acceptance—mean total scores		
Model	(4) Low risk	(5) Medium risk	(6) High risk
(Intercept)	−0.286	0.282	1.649***
	(0.242)	(0.221)	(0.264)
Age	0.010***	0.002	−0.013***
	(0.003)	(0.003)	(0.003)
AI familiarity	0.533***	0.176	−0.239*
	(0.120)	(0.119)	(0.104)
Education	0.057	0.046	−0.163***
	(0.040)	(0.042)	(0.049)
Female gender	0.115	0.107	0.044
	(0.075)	(0.074)	(0.084)
Digital competency	0.226***	0.108*	−0.033
	(0.053)	(0.045)	(0.049)
Num.Obs.	999	999	999
R^2	0.590	0.574	0.482
R^2 Adj	0.588	0.572	0.479
RMSE	1.12	1.14	1.30

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

settings ($B = -0.013$, $p < 0.001$). Interestingly, *education* level had no significant effect in low- and medium-risk settings, but was strongly negatively related to AI acceptance in high-risk contexts ($B = -0.163$, $p < 0.001$), indicating that more educated individuals may be more skeptical of AI applications in high-stakes environments. While *AI familiarity* was positively associated with AI acceptance in low-risk settings ($B = 0.533$, $p < 0.001$), its effect weakened in medium-risk conditions ($B = 0.176$, n.s.) and turned negative in high-risk contexts ($B = -0.239$, $p < 0.05$). This suggests that individuals familiar with AI may be more critical of its application in high-risk domains. In addition, *digital competency* was only positively related to AI acceptance in low- ($B = 0.226$, $p < 0.001$) or medium-risk contexts ($B = 0.108$, $p < 0.05$) while showing no significant effect in the high-risk context. Removing AI attitude as a predictor decreased R^2 by 35–40% across models (not shown in table). An alternative specification with AI attitude factor scores as a predictor did not yield meaningfully different results (see Appendix A11).

Finally, we assessed *attitude strength (extremity)* and *C–A inconsistency* as moderators of the relationship between AI attitudes and AI acceptance. Appendix A12 shows the extended versions of models 4) to 6). Each moderator on its own showed a significant effect consistent with prior literature (Krosnick and Petty 1995; Conner et al. 2021): *extremity* was a positive moderator across low, medium ($p < 0.05$) and high risk ($p < 0.01$) settings. Similarly, *C–A inconsistency* had a negative effect in all risk conditions, but was highly significant in low- and high-risk settings ($p < 0.01$) while only being barely significant in the medium risk setting ($p < 0.1$). When adding both moderators, only C–A inconsistency remained barely significant in low- and high-risk contexts ($p < 0.1$). Noticeably, R^2 increased only by up to 1% when adding moderators compared to Appendix A11. Significance levels and direction of coefficient estimates for other independent variables did not shift meaningfully due to added moderators.

Assessment of regression assumptions for models 1) to 6) largely alleviated concerns regarding autocorrelation, collinearity, and outliers. The Durbin–Watson test for autocorrelation yielded mostly insignificant results, except for model 2) (DW = 1.864, $p = 0.037$). The Variance Inflation Factor (VIF) was < 1.7 for all predictors, indicating no problematic collinearity. Maximum Cook's distance values ranged from 0.011 to 0.055, well below the threshold of 1, suggesting no single observation unduly influenced the model. However, assumptions of homoscedasticity and normality of residuals were not met, which is common when conducting regression analyses on bounded variables. The Breusch–Pagan test revealed significant heteroscedasticity across all specifications ($p < 0.05$ for models 1–3 and $p < 0.001$ for models 4–6). In addition, the Shapiro–Wilk test indicated non-normality of residuals across models ($W > 0.97$, $p < 0.01$). These results led us to report robust standard errors.

7 Discussion

In this section, we discuss our findings in detail, focusing on (1) the psychometric properties of our newly developed AI attitude scale, (2) observed patterns in AI attitude and acceptance across demographic groups in Germany and (3) the study's limitations plus avenues for future research.

7.1 Scale psychometrics and validation

Our findings support the proposed AI attitude scale as a concise and psychometrically sound instrument, aligned with a unidimensional, multi-faceted perspective on attitudes. Using techniques from both CTT and IRT, we found both high reliability and validity across two samples. Global fit indices from CFA met or exceeded standard criteria for model fit and all six items loaded strongly on a single factor. Similarly, IRT analyses suggested that our short scale assessed general AI attitude on a broad spectrum of approval most commonly held in the general population. Finally, we established criterion validity through regression analyses, showing that the scale was a predictor for AI acceptance and correlated positively with digital competency while revealing no meaningful correlations with unrelated concepts. By incorporating items that tap into the affective, behavioral and cognitive facets of attitudes, the scale is the first concise yet conceptually holistic measurement instrument for AI attitude. Moreover, the general nature of its items supports its application as AI evolves further, enabling large, repeated measurements to track AI attitudes over time.

To our knowledge, this study is the first to develop an AI attitude scale leveraging both CTT and IRT, providing a detailed psychometric evaluation. While the scale demonstrated promising measurement properties and no meaningful DIF across *gender* or *age* groups, IRT analyses also suggested potential gaps in measurement precision at both very low and very high levels of latent AI attitude. This means that additional items targeting extreme positions could further improve the scale's coverage. However, given that no prior AI attitude studies have used IRT modeling for evaluation, comparisons with existing scales were not possible.

In addition, a floor effect was observed for the AI attitude scale in the German sample, with a subset of participants consistently selecting the lowest response option. Notably, half of these respondents did not report prior knowledge of AI, which could imply that these are more skeptical of its application or benefits. This compression at the low end may hinder the detection of meaningful variance among individuals with strong opposition to or no prior knowledge of AI, which may be relevant from a policy perspective. Part of the floor effect may also stem from satisficing behavior and response patterns, such as "straightlining", the minimization of cognitive effort by selecting extreme or repetitive answers (Krosnick 1991). Both phenomena may also be linked to our design omitting reverse-coded items and using consistent labels across items. We acknowledge these limitations in favor of reduced cognitive complexity, method bias, and improved measurement invariance.

Finally, our results reinforce the theoretical role of attitudes in shaping behavioral intentions (Ajzen et al. 2018), demonstrating that the scale was strongly and significantly related to our AI acceptance measure based on Koenig (2024) across diverse scenarios and risk contexts. This shows that general attitudes can have strong predictive power, underscoring the relevance of the construct (Montag and Ali 2025a).

7.2 AI attitudes and acceptance across demographic groups in Germany

We examined which individual characteristics are associated with different attitudes towards AI among our volunteer panel of German internet users, and how these relate to the acceptance of AI applications. Our regression analyses revealed several significant predictors of AI attitude, including positive (*AI familiarity*, *education*, *digital competency*, and *job satisfaction*) and negative effects (*age* and *female gender*). While we hope to shed more light on the mixed evidence from prior research, differences may also be attributable to varying control variables (e.g., inclusion of psychological constructs in Stein et al. 2024) and national cultures. Compared to the only AI attitude scale developed with a German sample by Sindermann et al. (2021), we again found a negative influence of *female gender*, and additionally for *age*, which they found not to be significant. This indicates that older and female citizens may tend to hold more negative attitudes towards AI, possibly due to higher levels of technology or risk aversion. Finally, *job satisfaction* emerged as the only significant predictor not identified in prior studies. The positive effect suggests that people content in their jobs might feel less threatened by AI automation, whereas those dissatisfied or insecure might fear AI as a competitor or disruptor in the workplace.

Using a measure of AI acceptance for applications in varying risk contexts, our findings affirm a strong link between general attitude and behavioral intentions, measured via acceptance of AI, supporting classic theories such as the TPB (Ajzen 1985, 1991). AI attitude scores were powerful predictors of approval across all AI use cases we presented. The regression models showed that AI attitude alone explained a substantial portion of variance in AI acceptance (ΔR2 between 36 and 41%), also speaking for the strength of our attitude measure. In practical terms, participants general outlook on AI translated strongly into their opinions on deploying AI and may serve as an early policy indicator:

deteriorating general attitudes could predict growing resistance to new AI deployments, whereas optimistic attitudes might facilitate the introduction of AI innovations. Thus, policymakers could monitor AI attitudes over time to detect shifts in opinion related to real-world AI incidents or breakthroughs, thereby informing decision-making.

However, even among those with generally positive AI attitude, AI acceptance was not indiscriminate. The strong attitude–acceptance correlation thus reflects a baseline inclination, modulated by the specifics of each use case. As an example, while prior studies identified a positive or no effect of higher *education* on AI acceptance (see Grassini 2023; Schepman and Rodway 2023; Ismatullaev and Kim 2024), we found that this is moderated by risk, with higher levels of education leading to lower approval of high-risk AI applications. A similar moderating effect was also observed for *AI familiarity* and *digital competency*. It appears that well-informed and technology–savvy participants may be more aware of AI's risks and shortcomings, approving of AI for benign uses but drawing a hard line at applications they deem too sensitive. These results highlight the nuanced nature of AI attitudes, as well as the need for context-dependent AI acceptance measures capturing specific behavioral responses.

In addition to risk-related moderation, we also found theoretically consistent moderating effects of attitude strength and structural ambivalence. As predicted by prior theory, extremity significantly amplified the relationship between general AI attitude and acceptance across all risk levels, in line with the idea that stronger attitudes more reliably predict behavior (Krosnick and Petty 1995). In contrast, *C–A* inconsistency weakened this relationship, indicating that internal evaluative conflict impairs the translation of attitude into behavioral intention. Although both moderators were individually significant, only ambivalence remained marginally significant when both were entered simultaneously, and additional explained variance was modest ($\Delta R^2 \approx 1\%$). While this implies a minor role of these moderators, it also shows that structural ambivalence can be modelled with a unidimensional, bipolar scale, and does not necessitate a bivariate measurement model.

7.3 Limitations and future research

Naturally, this study has several limitations, opening avenues for future research. Two overarching issues that also affect previous AI attitude studies relate to the complex nature of the concept, and our non-probability samples. First, given AI has historically lacked a common definition (Goertzel and Achler 2014; Kelly et al. 2023) and is evolving so quickly, it is hard to ensure that survey respondents have a common conception of it, and thus for researchers to establish content validity. Future surveys could address this by including open-ended questions about participants' conceptions and opinions of AI, enabling comparisons of mental models and technological awareness (Szafran and Bach 2024). These should also continue to include further measures to infer attitude strength, such as AI familiarity, literacy, or actual usage behavior. Second, although our samples were sizable and balanced through quotas, both relied on non-probability online volunteer panels. Consequently, certain groups—such as individuals less active online—were under-represented and self-selection biases may have influenced the results. Moreover, we tested the scale in two samples from Western countries. Given variations in AI literacy, availability of advanced AI models, and media coverage across countries and cultural contexts, respondents' conceptualizations of AI likely differ internationally. As suggested by Montag et al. (2024), we thus encourage further replications and studies on AI attitudes in representative cross-cultural contexts, which would allow more robust inferences about diverse populations. To meaningfully compare AI attitude scores between different contexts, however, measurement invariance would need to be carefully assessed. As a starting point, this may include estimating sequences of constrained multi-group CFAs to assess configural, metric and scalar invariance (Schoot et al. 2012). These tests may be accompanied by modern algorithmic approaches for detecting group differences and estimating latent variable scores under parameter heterogeneity (Brandmaier et al. 2013; Classe and Kern 2024a, b).

Furthermore, while the brevity of our short scale is advantageous, it also entails important trade-offs. The scale exhibited reduced sensitivity at the extremes, especially for respondents without prior knowledge of AI in the German sample, who often selected the most negative response option. This suggests the scale may not fully distinguish degrees of strong AI skepticism or fear, potentially due to its positive framing after exclusion of reverse-scored items from Stein et al. (2024). Although this reduces method bias (Podsakoff et al. 2003), it may inadvertently induce an acquiescence bias or straight-lining behavior, and not fully capture negative attitudes. Such criticism has also been raised by Schepman and Rodway (2025) for the positively-worded agreement scale by Grassini (2023). We further acknowledge the risk of inflated reliability due to including solely positively framed items. Future research might address this by adding items targeting the low end of the attitude spectrum, or testing whether item-specific negative and positive labels would improve measurement properties.

We also see opportunities for extended statistical analyses and replications. We utilized a self-developed AI acceptance measure following Koenig (2024) which had not been validated in prior studies, as we did not find established holistic measures. We urge following studies to further validate our AI acceptance index and examine the relationship of AI attitudes with actual usage behavior to evaluate whether the scale remains a consistent predictor. While we conceptualized AI attitudes and acceptance as two distinct constructs, their sequential placement in the German survey may have introduced empirical overlap, reinforcing our call for further replications. Furthermore, due to survey length constraints, our regression analyses could not include an exhaustive set of control variables, which may have influenced the significance of predictors, such as *gender* or *age*. Future research should incorporate a broader range of controls to determine whether the effects of these demographics persist or are mediated by other factors. Finally, given the cross-sectional and correlational nature of our regression analyses, causal inferences are limited. Longitudinal studies are needed to disentangle cause and effect, and to explore how individual attitudes evolve over time or in response to increased exposure to AI. As AI becomes more ubiquitous and its capabilities continue to evolve, we expect that public attitudes will shift accordingly—underscoring the value of a short scale for tracking these changes in survey panels.

8 Conclusion

We developed and validated a concise, psychometrically sound six-item instrument for measuring general AI attitude. We further highlighted both the importance of attitudes in shaping behavior, as well as the nuanced patterns driving societal acceptance of AI applications. As AI becomes increasingly embedded in our lives, regular measurements of AI attitudes in the population is paramount. Our short scale enables researchers to include the construct in more studies and thus reliably track public sentiment with minimal respondent burden, ultimately providing valuable insights for policymakers. We encourage further research on AI attitudes across different countries and over time to build a comparative, global knowledge base on how public sentiment shapes and is shaped by the integration of AI into daily life.

Appendix

A1 Introduction to AI by Stein et al. (2024)

German version (used in survey)	English version
Im Folgenden interessieren wir uns für Ihre Einstellungen gegenüber Künstlicher Intelligenz (KI). Künstliche Intelligenz kann Aufgaben ausführen, die üblicherweise menschliche Intelligenz erfordern. Sie befähigt Maschinen dazu, selbstständig und ähnlich dem Menschen, ihre Umwelt wahrzunehmen, zu handeln, zu lernen und sich anzupassen. Künstliche Intelligenz kann Teil eines Computers oder einer Onlineplattform sein—man kann ihr aber auch in verschiedenen anderen technischen Geräten, wie etwa Robotern, begegnen	In the following, we are interested in your attitudes towards artificial intelligence (AI). AI can execute tasks that typically require human intelligence. It enables machines to sense, act, learn, and adapt in an autonomous, human-like way. AI may be part of a computer or online platform—but it can also be encountered in various other hardware devices, such as robots

A2 SQP quality estimates

Comparison of SQP quality estimates between Stein et al. (2024) and our adapted items.

Stein et al. (2024)		Our scale	
Item	Quality (q2)	Item	Quality (q2)
Künstliche Intelligenz wird die Welt verbessern	0.51	Inwieweit sind Sie der Meinung, dass künstliche Intelligenz die Welt verbessern wird?	0.56
Ich möchte Technologien nutzen, die auf künstlicher Intelligenz basieren	0.53	Wie sehr möchten Sie Technologien nutzen, die auf künstlicher Intelligenz basieren?	0.56
Ich freue mich auf zukünftige Entwicklungen im Bereich künstliche Intelligenz	0.58	Wie sehr freuen Sie sich auf zukünftige Entwicklungen im Bereich künstliche Intelligenz?	0.60
Künstliche Intelligenz bietet Lösungen für viele globale Probleme	0.52	Inwieweit glauben Sie, dass künstliche Intelligenz Lösungen für globale Probleme bietet?	0.56

Stein et al. (2024)		Our scale	
Item	Quality (q2)	Item	Quality (q2)
Wenn ich an künstliche Intelligenz denke, habe ich hauptsächlich positive Gefühle	0.54	Haben Sie hauptsächlich positive Gefühle, wenn Sie an künstliche Intelligenz denken?	0.60
Ich würde mich eher für eine Technologie mit künstlicher Intelligenz entscheiden als für eine ohne	0.50	Inwieweit würden Sie sich eher für eine Technologie mit künstlicher Intelligenz entscheiden als für eine ohne?	0.56

A3 AI acceptance risk scenarios

Scenario	German original (used in survey)	English translation
#1—Low risk (translation)	Künstlich intelligente Systeme können eingesetzt werden, um Text in Echtzeit in andere Sprachen zu übersetzen. Das kann es ermöglichen, mit anderen Menschen zu kommunizieren, deren Sprache man nicht beherrscht. Künstliche Intelligenz wird dabei verwendet, um eine automatische Übersetzung mit hoher Geschwindigkeit zu ermöglichen. Das System lernt diese Fähigkeit von einem großen Datensatz mit Beispielen bestehender Übersetzungen (bspw. auf Deutsch und Englisch veröffentlichte Bücher)	Artificially intelligent systems can be used to translate text into other languages in real time. This can make it possible to communicate with other people whose language one does not speak. Artificial intelligence is employed in this context to enable automatic translation at high speed. The system learns this ability from a large data set of examples of existing translations (e.g., books published in German and English)
#2—Medium risk (legal documents analysis)	Künstlich intelligente Systeme können eingesetzt werden, um rechtliche Dokumente wie Verträge automatisch zu analysieren. Dabei kann sich bspw. ein Verbraucher vor Abschluss eines Onlinekaufs die allgemeinen Geschäftsbedingungen des Händlers zusammenfassen lassen, um Risiken zu identifizieren. Künstliche Intelligenz wird dabei verwendet, um große Textmengen automatisch zu analysieren. Das System lernt diese Fähigkeit von einem großen Datensatz mit Gesetzestexten und Beispielen bestehender Verträge	Artificially intelligent systems can be used to automatically analyze legal documents such as contracts. For example, a consumer can have the retailer's general terms and conditions summarized before concluding an online purchase in order to identify risks. Artificial intelligence is employed in this context to automatically analyze large volumes of text. The system learns this skill from a large data set of legal texts and examples of existing contracts

Scenario	German original (used in survey)	English translation
#3—High risk (Psychological counseling)	Künstlich intelligente Systeme können eingesetzt werden, um Menschen via Chat psychologisch zu beraten. Das kann es ermöglichen, zu jeder Tages- und Nachtzeit die eigenen Anliegen mitzuteilen und Ratschläge zu erhalten, auch wenn man bspw. noch keinen Therapieplatz hat. Künstliche Intelligenz wird dabei verwendet, um Probleme automatisch einzuordnen und Ratschläge zu geben. Das System lernt diese Fähigkeit von einem großen Datensatz aus Protokollen psychologischer Gespräche und Gutachten	Artificially intelligent systems can be used to psychologically counsel people via chat. This can make it possible to communicate one's concerns and receive advice at any time of day or night, even if one does not yet have an assigned therapy spot, for example. Artificial intelligence is employed in this context to automatically classify problems and give advice. The system learns this ability from a large transcript data set of psychological interviews and assessments

A4 Overview of further survey items

Variables/items	German question	English translation
Age	Wie alt sind sie?	How old are you?
AI familiarity	Sind Ihnen die Begriffe „künstliche Intelligenz " oder „KI " (sprich „ka-ie ") vertraut?	Are you familiar with the terms "artificial intelligence" or "AI" (pronounced "A-I")?
Digital competency (Herklotz and Haensch 2025)		
Question	Wie sicher fühlen Sie sich beim Umgang mit den folgenden Aufgaben am Computer (Laptop, Desktop)?	How confident do you feel in performing the following tasks on a computer (laptop, desktop)?
Item #1	Dateien über den Dateipfad finden	Finding files using the file path
Item #2	Dateien über den Such–Befehl finden	Finding files using the search function
Item #3	Dateimanagement (Kopieren, Ausschneiden, Einfügen, Löschen und Umbenennen von Dateien)	File management (copying, cutting, pasting, deleting, and renaming files)
Item #4	Dateien aus dem Internet herunterladen und speichern (beispielsweise Text, Bilder, PDF, …)	Downloading and saving files from the internet (e.g., text, images, PDFs, etc.)
Item #5	Eine App oder ein Programm aus dem Appstore oder Microsoft Store laden	Downloading an app or program from the App Store or Microsoft Store
Item #6	Ein Programm installieren	Installing a program
Education	Welchen höchsten allgemeinbildenden Schulabschluss haben Sie?	What is the highest level of general education you have completed?
Employment level	Welche Erwerbssituation trifft derzeitig auf Sie zu?	What is your current employment status?
Female gender	Sind Sie männlich, weiblich, oder anderes?	Are you male, female, or another gender?
Household income *(monthly net income)*	Wie hoch ist das durchschnittliche monatliche Netto-Einkommen Ihres Haushaltes insgesamt? *Damit ist die Summe gemeint, die nach Abzug der Steuern und Sozialversicherungsbeiträge zusammengerechnet für alle Personen, die in Ihrem Haushalt leben, übrig bleibt*	What is the total average monthly net income of your household? *This refers to the total amount remaining for all persons living in your household after deducting taxes and social security contributions*
Job satisfaction		
Item #1	Wenn ich noch einmal zu entscheiden hätte, würde ich wieder den gleichen Beruf wählen	If I had to decide again, I would choose the same profession
Item #2 (neg.)	Meine Arbeit macht mir wenig Spaß	I find little enjoyment in my work
Item #3	Insgesamt ist meine Arbeit befriedigend	Overall, I am satisfied with my job
Item #4	Meine Arbeit gibt mir genügend Möglichkeiten, meine Fähigkeiten auszunutzen	My work provides me with sufficient opportunities to use my skills

Variables/items	German question	English translation
Job security (based on Fischer and Lück 1977)		
Item #1	Wie zuversichtlich sind Sie, dass Sie Ihren Arbeitsplatz in den nächsten 12 Monaten behalten werden?	How confident are you that you will keep your job in the next 12 months?
Item #2	Stellen Sie sich vor, Sie verlieren Ihren aktuellen Job. Wie zuversichtlich sind Sie, dass Sie innerhalb von sechs Monaten eine neue Arbeit finden würden?	Imagine you lose your current job. How confident are you that you would find a new job within 6 months?
Item #3	Wie zuversichtlich sind Sie, dass die Arbeitsbedingungen in Ihrem Berufsfeld in den nächsten Jahren gleich bleiben oder sich sogar verbessern werden?	How confident are you that working conditions in your field will remain stable or improve in the coming years?
Political orientation (GESIS 2023)	Viele Leute verwenden die Begriffe "links" und "rechts", wenn es darum geht, unterschiedliche politische Einstellungen zu kennzeichnen. Wo würden Sie Ihre eigenen politischen Ansichten einstufen?	Many people use the terms "left" and "right" to describe different political views. Where would you place your own political views?

A5 Robustness check: exploratory factor analysis and parallel analysis

As a robustness check, we conducted exploratory factor analysis (EFA) to evaluate whether a single factor structure would actually show best fit (DeVellis and Thorpe 2021). First, data suitability was evaluated using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (>0.5, acceptable) and Bartlett's test of sphericity ($p<0.05$, acceptable; Williams et al. 2010). Principal axis factoring (PAF) was used for factor extraction, with the optimal number of factors determined through parallel analysis (Horn 1965; Hayton et al. 2004). All analyses were performed in R using the psych package (version 2.4.6.26; Revelle 2024).

All EFA assumptions were met: in the German sample, the KMO measure was 0.93, while Bartlett's test of sphericity yielded a significant result [$\chi 2(15)=5662$, $p<0.001$], indicating excellent sampling adequacy and strong inter-item correlations. Parallel analysis supported a single-factor structure, as only the first factor's eigenvalue exceeded that from random data and the second eigenvalue merely equaling 0.07. The corresponding plot is reported below. Similar results were achieved for the US sample, where the results are also available in our R code.

As a further robustness check, we randomly split our data set into two subsets to conduct EFA and CFA on distinct data. Since this approach produced results consistent with the full sample (a single-factor structure and comparable CFA fit), we only report full sample findings in the paper. The auxiliary analysis can be found in our R code.

See Fig. 2

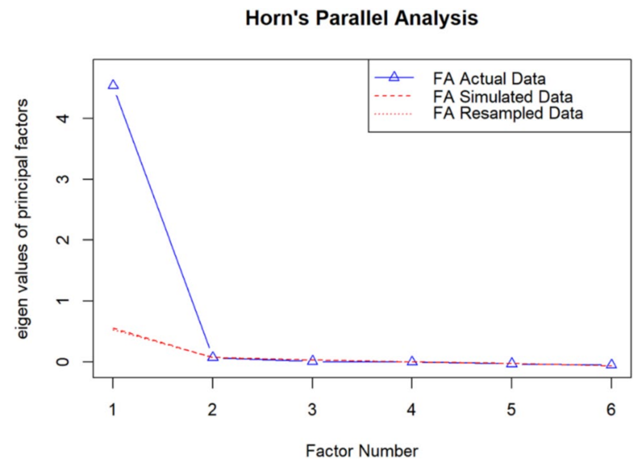

Fig. 2 Parallel Analysis results for the German sample

A6 Descriptive sample statistics

German sample ($n=1001$)

See Table 13, 14, and 15.

US sample ($n=3091$)

See Table 16, 17.

A7 Histograms for AI attitude and AI acceptance mean scores

See Figs. 3 and 4.

A8 Additional analyses of US sample—factorial structure

See Table 18 and 19.

Table 13 Overview of metric variables in our German sample

Variable		Mean	SD	Min	Max	Median	# NA
Developed measures							
AI attitude (Mean)		**3.8**	**1.6**	**1.0**	**7.0**	**4.0**	**0**
Item #1		3.8	1.7	1.0	7.0	4.0	0
Item #2		3.9	1.8	1.0	7.0	4.0	0
Item #3		3.8	1.9	1.0	7.0	4.0	0
Item #4		3.8	1.8	1.0	7.0	4.0	0
Item #5		3.6	1.7	1.0	7.0	4.0	0
Item #6		3.8	1.7	1.0	7.0	4.0	0
AI acceptance –	Low risk (Mean)	**4.5**	**1.8**	**1.0**	**7.0**	**4.7**	**0**
	Item #1	4.9	1.9	1.0	7.0	5.0	0
	Item #2	4.2	1.9	1.0	7.0	4.0	0
	Item #3	4.5	1.8	1.0	7.0	5.0	0
	Medium risk (Mean)	**4.2**	**1.8**	**1.0**	**7.0**	**4.3**	**0**
	Item #1	4.3	1.9	1.0	7.0	5.0	0
	Item #2	3.9	1.8	1.0	7.0	4.0	0
	Item #3	4.2	1.8	1.0	7.0	4.0	0
	High risk (Mean)	**3.4**	**1.8**	**1.0**	**7.0**	**3.7**	**0**
	Item #1	3.5	1.9	1.0	7.0	4.0	0
	Item #2	3.2	1.9	1.0	7.0	3.0	0
	Item #3	3.6	1.9	1.0	7.0	4.0	0
AI attitude—moderators							
Cognitive–affective (C–A) inconsistency		1.4	1.2	0.0	6.0	1.0	0
Extremity		1.3	1.0	0.0	3.0	1.0	0
Other measures							
Age		43.2	13.7	18.0	64.0	44.0	0
AI familiarity		0.8	0.4	0.0	1.0	1.0	0
Digital competency		3.9	0.9	1.0	5.0	4.0	0
Education		2.7	0.9	0.0	4.0	2.0	0
Employment		2.9	1.3	1.0	4.0	3.0	16
Female gender		0.5	0.5	0.0	1.0	1.0	2
Household income		4.5	1.6	1.0	7.0	4.0	71
Job satisfaction		3.3	0.7	1.0	5.0	3.2	255
Job security		3.0	0.7	1.0	4.0	3.0	255
Political orientation		5.4	2.0	1.0	10.0	5.0	1

NA values arise due to nonresponse, or missing observations (i.e., job satisfaction and job security forunemployed participants

A9 Additional analyses of US sample—item response theory

GRM analysis for our US sample is reported in Table 20 and yielded results very similar to our German sample. All items showed high discrimination (>2.5) and difficulty parameters were distributed between −2.0 and +1.5. Model fit was excellent for SRMSR = 0.026 and CFI = 0.995, and adequate for RMSEA = 0.068, with RMSEA values at or below 0.02 for all individual items. We found high empirical and marginal reliability (both 0.95). Again, all key IRT assumptions were supported, with unidimensionality given by CFA and GRM model fit, local independence by Yen's (1984) Q3 (all values < 0.0), and Mokken scale analysis showing few significant deviations from monotonicity (ItemH > 0.70; Crit = 36) given our large sample size (n = 3091).

See Figs. 5, 6, and 7.

A10 Robustness check: regression results for AI attitude

Extended version of Table 11, but reporting standardized regression coefficients (β) and two alternative target variable operationalizations for AI attitude: mean total scores (b) and factor scores from CFA (c). Robust standard error in parentheses. Decreasing sample sizes are due to missing variable observations

Table 14 Overview of categorical variables and their coding into levels in our German sample

Variable	N	% of sample
AI familiarity		
[0] N/A	1	0.1%
[0] No	139	13.9%
[0] Not sure	37	3.7%
[1] Yes	824	82.3%
Gender		
[0] Male	492	49.2%
[1] Female	507	50.6%
[N/A] Other	2	0.2%
Education		
[0] N/A	2	0.2%
[1] Student/No School Degree	41	4.1%
[2] Lower Secondary Degree *("Hauptschulabschluss", 8th/9th grade)*	482	48.2%
[3] Intermediate Secondary Degree *("Realschulabschluss", 10th grade)*	172	17.2%
[4] Higher Education *("Abitur/Fachhochschulreife", 12th/13th grade)*	304	30.4%
Employment		
[1] Not Employed	255	25.5%
[2] Employed, Side Job	57	5.7%
[3] Employed, part-time	189	18.9%
[4] Employed, full-time	484	48.4%
N/A	16	1.6%
Household income *(monthly net income)*		
[1] Up to €520	45	4.5%
[2] €521 up to €750	39	3.9%
[3] €750 up to €1,500	180	18.0%
[4] €1,500 up to €2,500	228	22.8%
[5] €2,500 up to €3,500	157	15.7%
[6] €3,500 up to €5,000	173	17.3%
[7] €5,000 and more	108	10.8%
[N/A] Not sure/do not want to respond	71	7.1%

Numbers in brackets [] represent values used for numerical analysis (regression)

Target variable	AI attitude–mean total score			AI attitude—factor score		
Model	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
Age	−0.135***	−0.139***	−0.160***	−0.134***	−0.138***	−0.157***
	(0.029)	(0.029)	(0.036)	(0.029)	(0.029)	(0.036)
AI familiarity	0.246***	0.198***	0.164***	0.248***	0.200***	0.169***
	(0.031)	(0.032)	(0.042)	(0.031)	(0.032)	(0.042)
Education	0.175***	0.124***	0.077*	0.175***	0.124***	0.079*
	(0.030)	(0.032)	(0.039)	(0.030)	(0.032)	(0.039)
Female gender	−0.175***	−0.162***	−0.197***	−0.177***	−0.164***	−0.198***
	(0.028)	(0.028)	(0.035)	(0.028)	(0.028)	(0.035)
Digital competency		0.179***	0.203***		0.179***	0.201***
		(0.036)	(0.049)		(0.036)	(0.049)
Employment situation			−0.020			−0.014
			(0.039)			(0.039)
Household income			0.009			0.005
			(0.042)			(0.042)

Table 15 Correlation matrix for all measures in our German sample, with mean scores used for our developed measures

	Age	AI familiarity	Digital competency	Education	Employment	Female gender	Household income	Job satisfaction	Job security	Political orientation	AI attitude	AI Attitude—C-A-I	AI Attitude—Extremity	AI accept.—LR	AI accept.—MR	AI accept.—HR
Age	1															
AI familiarity	−0.19	1														
Digital competency	−0.11	0.34	1													
Education	−0.30	0.27	0.36	1												
Employment	−0.23	0.19	0.19	0.28	1											
Female gender	−0.10	−0.05	−0.13	−0.13	−0.17	1										
Household income	−0.13	0.29	0.28	0.43	0.53	−0.18	1									
Job satisfaction	0.00	0.05	0.25	0.18	0.10	−0.10	0.26	1								
Job security	−0.12	0.17	0.34	0.19	0.14	−0.07	0.35	0.43	1							
Political orientation	0.01	0.07	−0.03	−0.07	0.05	−0.08	0.05	−0.02	0.05	1						
AI attitude	−0.22	0.33	0.33	0.30	0.20	−0.20	0.26	0.16	0.25	0.03	1					
Mod: C–A–I	−0.02	0.09	0.08	0.00	−0.05	−0.07	0.02	0.03	0.02	−0.07	0.14	1				
Mod: Extremity	0.08	−0.18	−0.09	−0.09	−0.09	0.01	−0.10	0.07	0.02	0.12	−0.29	−0.26	1			
AI accept.—LR	−0.12	0.37	0.38	0.28	0.19	−0.13	0.27	0.14	0.29	0.03	0.74	0.19	−0.31	1		
AI accept.—MR	−0.16	0.30	0.31	0.27	0.20	−.13	0.24	0.12	0.24	0.01	0.75	0.16	−0.24	0.78	1	
AI accept.—HR	−0.21	0.17	0.18	0.14	0.16	−0.10	0.14	0.09	0.13	0.08	0.68	0.05	−0.18	0.54	0.63	1

Note: *LR* (low risk), *MR* (medium risk) and *HR* (high risk) refer to AI acceptance risk scenarios. *Mod* denotes our two AI attitude moderators, C-A inconsistency and extremity.

Table 16 Overview of metric variables in our US sample. For our AI Attitude scale, individual item scores are presented additionally

Variable	Mean	SD	Min	Max	Median	# NA
Developed measures						
AI attitude (Mean)	4.5	1.5	**1.0**	**7.0**	**4.7**	**0**
Item #1	4.6	1.5	1.0	7.0	5.0	0
Item #2	4.5	1.6	1.0	7.0	5.0	0
Item #3	4.7	1.7	1.0	7.0	5.0	0
Item #4	4.5	1.6	1.0	7.0	5.0	0
Item #5	4.3	1.7	1.0	7.0	5.0	0
Item #6	4.3	1.7	1.0	7.0	4.0	0
Others						
Age	46.0	15.7	18.0	86.0	47.0	139
AI familiarity	1.0	0.0	0.0	1.0	1.0	0
Female gender	0.5	0.5	0.0	1.0	1.0	139

NA values arise due to nonresponse

Table 17 Overview of categorical variables and their coding into levels in our US sample

Variable	N	% of sample
AI familiarity		
[0] No	2	< 0.1%
[0] I do not know	2	< 0.1%
[1] Yes	3087	99.9%
Gender		
[0] Male	1426	46.1%
[1] Female	1526	49.4%
[N/A] No response/consent revoked	139	4.6%

Numbers in brackets [] represent values used for numerical analysis

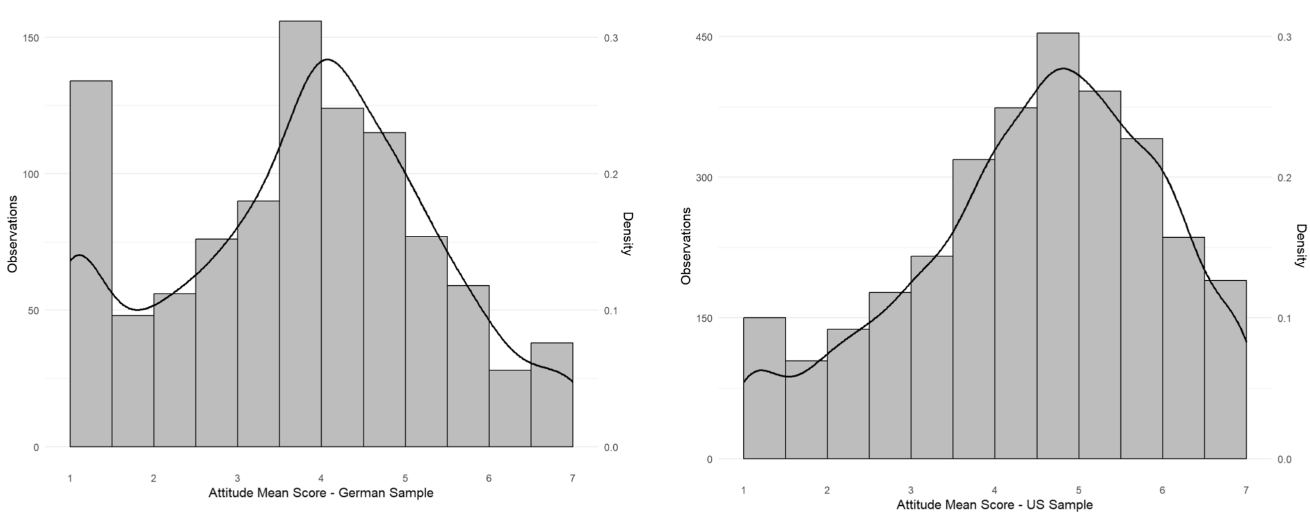

Fig. 3 AI attitude mean scores in Germany (left) and US (right). Histogram (binwidth = 0.5) and density plot

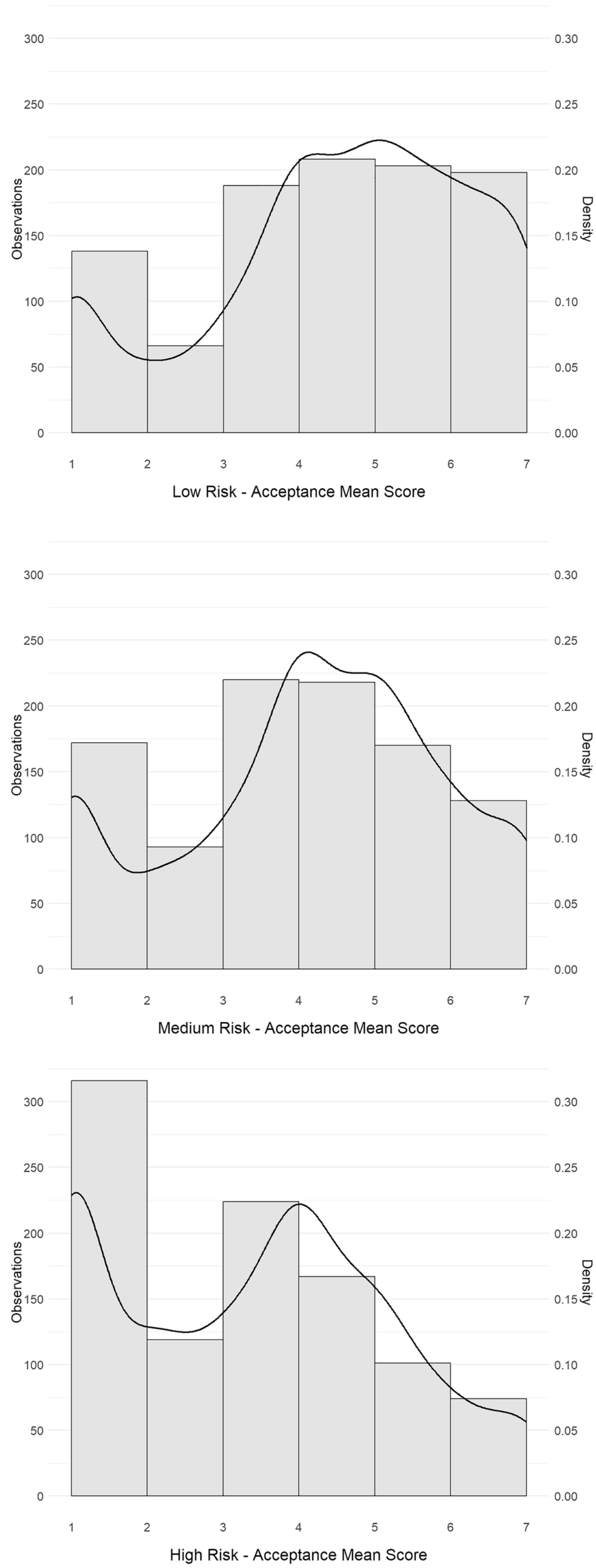

Fig. 4 AI acceptance mean scores in German sample. Histograms ▶ (binwidth = 1.0) and density plots in low-, medium- and high-risk context. *Note: A larger bin width is selected to account for the limited number of unique mean scores, which result from only three items and exhibit a higher degree of clustering*

Table 18 Factor loadings for AI attitude scale—(a) unidimensional model, US sample

Item	Unstandardized estimates				Standardized estimates	
	Loading on general factor (Std. error)	95% CI Lower	95% CI Upper	Residual variance	Loading on general factor	Residual variance
#1	1.33 (0.02)	1.29	1.37	0.43	0.90	0.20
#2	1.46 (0.02)	1.42	1.50	0.49	0.90	0.19
#3	1.60 (0.02)	1.56	1.64	0.47	0.92	0.15
#4	1.38 (0.02)	1.34	1.43	0.80	0.84	0.29
#5	1.56 (0.02)	1.52	1.60	0.56	0.90	0.19
#6	1.34 (0.03)	1.29	1.40	1.07	0.79	0.37

Table 19 Standardized factor loadings for our AI attitude scale, US sample, and alternative model specifications: (b) correlated facets, (c) bifactor S-1 model

Item	(b) Correlated facets				(c) Bifactor S-1			
asffg	Affective	Behavioral	Cognitive	Residual variance	General Factor	Affective	Cognitive	Residual variance
#1			0.91	0.17	0.89		0.11	0.19
#2		0.91		0.17	0.90			0.19
#3	0.92			0.15	0.92	0.00		0.15
#4			0.85	0.28	0.83		0.30	0.21
#5	0.90			0.18	0.90	0.17		0.15
#6		0.80		0.36	0.79			0.37

Table 20 Graded response model (GRM) for AI attitude, US sample

		Difficulty thresholds					
Item	Discrimination	T1	T2	T3	T4	T5	T6
#1	4.318	−2.042	−1.417	−0.857	−0.146	0.663	1.35
#2	4.366	−1.793	−1.166	−0.664	−0.068	0.634	1.297
#3	4.911	−1.705	−1.122	−0.706	−0.259	0.354	1.012
#4	3.095	−1.811	−1.201	−0.709	−0.091	0.623	1.433
#5	4.512	−1.485	−0.963	−0.537	−0.004	0.617	1.321
#6	2.876	−1.662	−1.037	−0.551	0.148	0.724	1.487

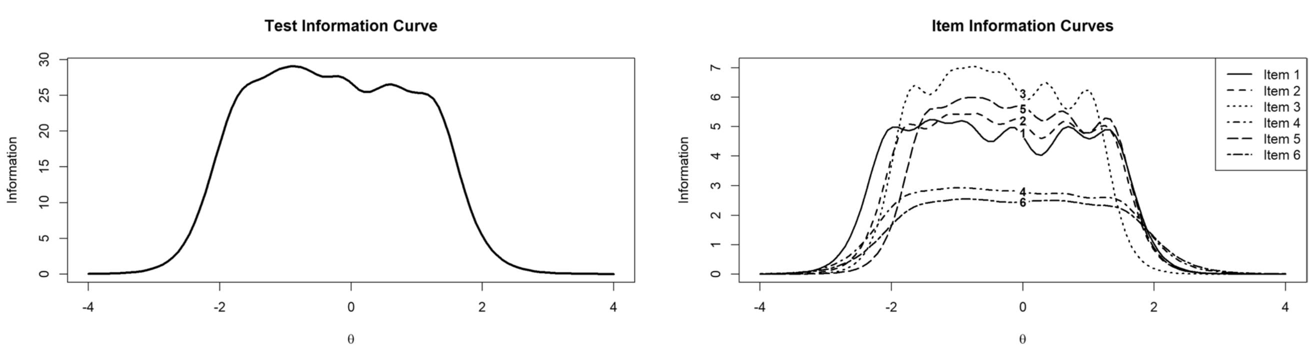

Fig. 5 Test (left) and item information curves (right) for AI attitude in our US sample

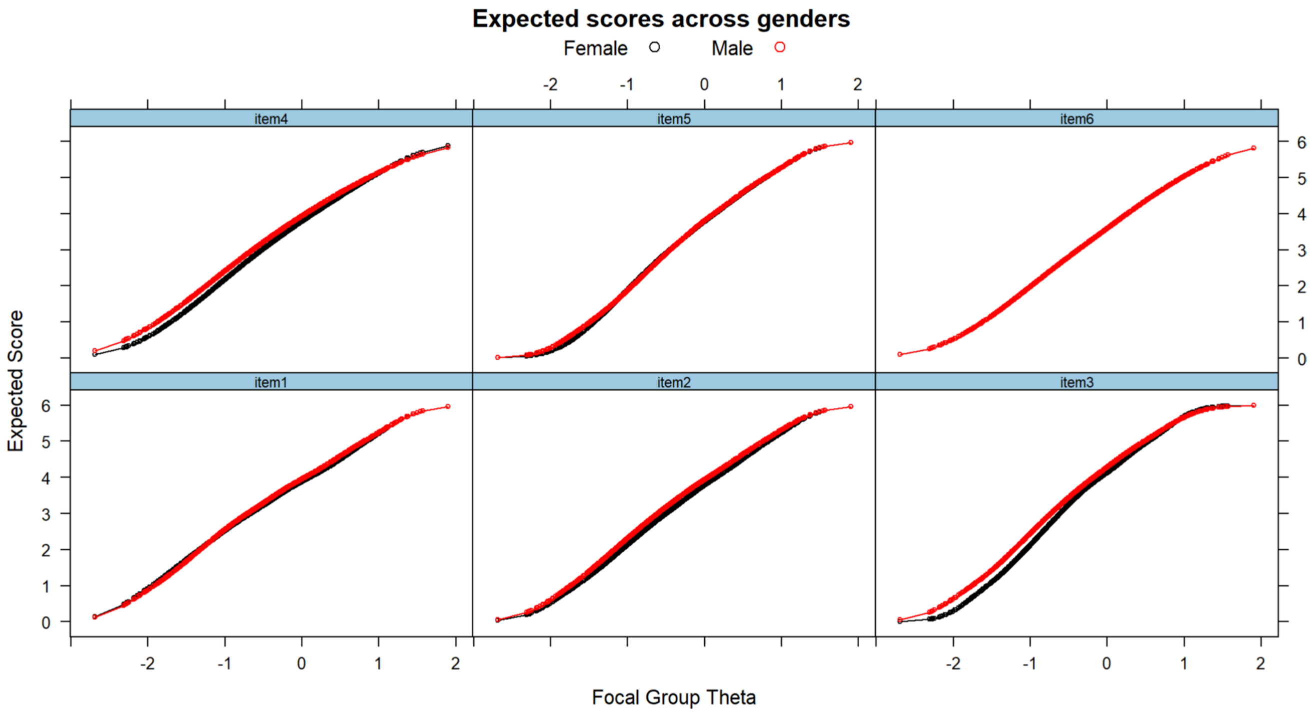

Fig. 6 Expected scores across genders for the AI attitude scale in our US sample. Females are shown in black, males in red

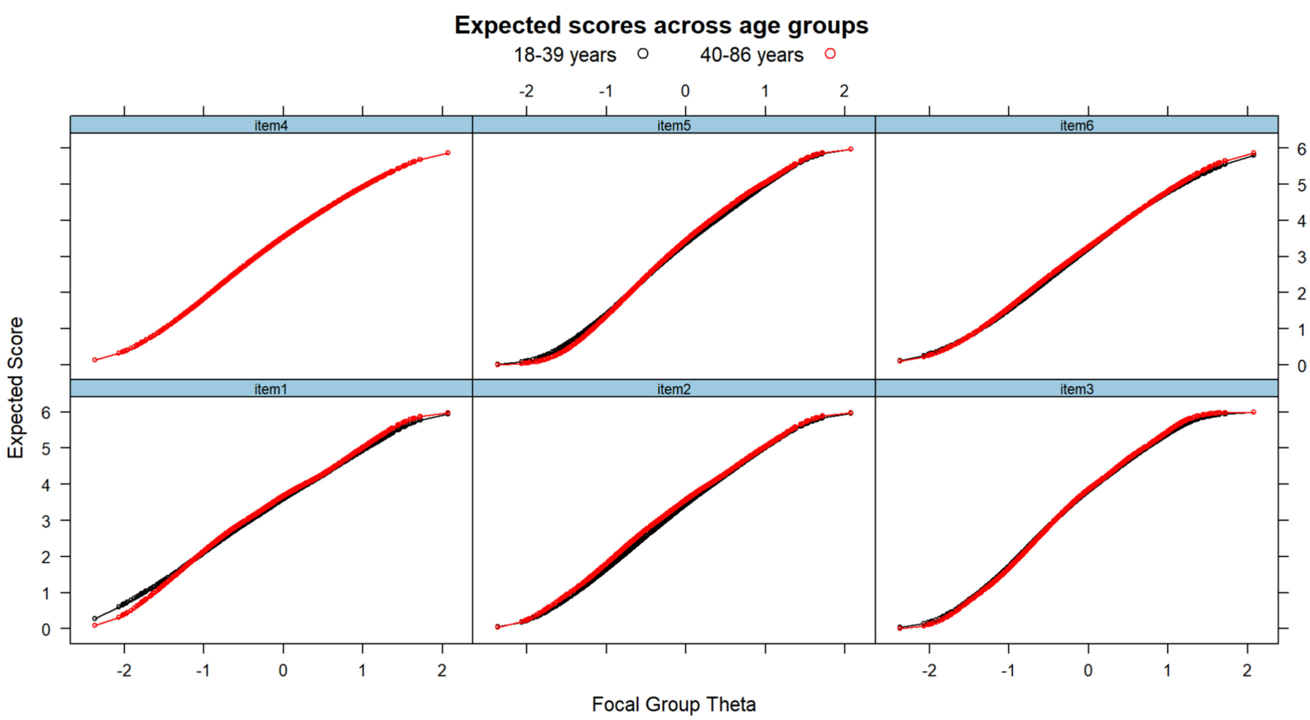

Fig. 7 Expected scores across age groups for the AI attitude scale in our US sample. Ages 18–39 are shown in black, ages 40–86 in red

Target variable	AI attitude–mean total score			AI attitude—factor score		
Model	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
Job satisfaction			0.014			0.013
			(0.044)			(0.044)
Job security			0.103*			0.105*
			(0.048)			(0.048)
Political orientation			0.063 +			0.064 +
			(0.038)			(0.038)
Num.Obs	999	999	675	999	999	675
R2	0.198	0.223	0.247	0.199	0.225	0.249
R2 Adj	0.194	0.219	0.235	0.196	0.221	0.238
RMSE	1.42	1.39	1.35	0.87	0.86	0.83

$+ p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A11 Robustness check: regression results for AI acceptance

Extended version of Table 12, but reporting standardized regression coefficients (β) and two alternative operationalizations for the independent variable AI attitude: mean total scores (b) and factor scores from CFA (c). Robust standard error in parentheses

Target variable	AI acceptance—mean total scores					
AI attitude operationalization	Mean total score			Factor score		
Model	(4b) Low risk	(5b) Medium risk	(6b) High risk	(4c) Low risk	(5c) Medium risk	(6c) High risk
Age	0.077***	0.018	−0.095***	0.076***	0.017	−0.096***
	(0.022)	(0.022)	(0.025)	(0.022)	(0.022)	(0.025)
AI familiarity	0.116***	0.038	−0.051*	0.115***	0.037	−0.052*
	(0.026)	(0.026)	(0.022)	(0.026)	(0.026)	(0.022)
Education	0.031	0.025	−0.086***	0.031	0.025	−0.085**
	(0.021)	(0.023)	(0.026)	(0.022)	(0.023)	(0.026)
Female gender	0.033	0.030	0.012	0.034	0.031	0.013
	(0.021)	(0.021)	(0.023)	(0.022)	(0.021)	(0.023)
Digital competency	0.120***	0.057*	−0.017	0.119***	0.057*	-0.017
	(0.028)	(0.024)	(0.025)	(0.028)	(0.024)	(0.025)
AI attitude—mean total score	0.681***	0.724***	0.713***			
	(0.026)	(0.024)	(0.026)			
AI attitude—factor score				0.680***	0.722***	0.710***
				(0.027)	(0.024)	(0.026)
Num.Obs	999	999	999	999	999	999
R2	0.590	0.574	0.482	0.589	0.571	0.479
R2 Adj	0.588	0.572	0.479	0.587	0.568	0.475
RMSE	1.12	1.14	1.30	1.12	1.15	1.30

$+ p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A12 Strength and C–A inconsistency as moderators of the AI attitude–acceptance relationship

Extended regression results with moderators for the AI attitude–AI acceptance relationship across risk contexts (*LR* Low risk, *MR* Medium risk, *HR* High risk). Based on models 4c–6c in Appendix A11. Sequentially introducing C–A inconsistency (C–A–I) and attitude strength (extremity) as moderators. Standardized regression coefficients reported, with robust standard error in parentheses

Target variable	AI acceptance—mean total scores								
Moderators	One moderator: C–A–I			One moderator: extremity			Both moderators		
Model	(4d) LR	(5d) MR	(6d) HR	(4e) LR	(5e) MR	(6e) HR	(4f) LR	(5f) MR	(6f) HR
Age	0.076***	0.017	−0.096***	0.074***	0.015	−0.099***	0.073***	0.015	−0.102***
	(0.022)	(0.022)	(0.025)	(0.022)	(0.022)	(0.025)	(0.022)	(0.022)	(0.025)
AI familiarity	0.115***	0.037	−0.052*	0.105***	0.034	−0.051*	0.103***	0.033	−0.051*
	(0.026)	(0.026)	(0.022)	(0.026)	(0.026)	(0.022)	(0.026)	(0.026)	(0.023)
Education	0.031	0.025	−0.085**	0.035 +	0.029	−0.081**	0.036 +	0.031	−0.088***
	(0.022)	(0.023)	(0.026)	(0.021)	(0.023)	(0.026)	(0.021)	(0.023)	(0.026)
Female gender	0.034	0.031	0.013	0.024	0.025	0.007	0.027	0.028	0.002
	(0.022)	(0.021)	(0.023)	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)
Digital competency	0.119***	0.057*	−0.017	0.121***	0.057*	−0.018	0.116***	0.053*	−0.018
	(0.028)	(0.024)	(0.025)	(0.028)	(0.024)	(0.025)	(0.027)	(0.024)	(0.025)
AI attitude—factor score	0.680***	0.722***	0.710***	0.496***	0.560***	0.511***	0.644***	0.651***	0.664***
	(0.027)	(0.024)	(0.026)	(0.075)	(0.076)	(0.081)	(0.098)	(0.101)	(0.119)
C–A–I	0.078***	0.055*	−0.046 +				0.062**	0.052*	−0.045
	(0.023)	(0.025)	(0.027)				(0.023)	(0.026)	(0.028)
Mod: AI attitude * C–A–I	−0.082**	−0.054 +	−0.099**				−0.061 +	−0.035	−0.079 +
	(0.029)	(0.031)	(0.034)				(0.035)	(0.038)	(0.044)
Extremity				−0.087***	−0.017	0.021	−0.066**	−0.001	0.019
				(0.021)	(0.021)	(0.023)	(0.021)	(0.022)	(0.023)
Mod: AI attitude * Extremity				0.165*	0.163*	0.212**	0.050	0.090	0.112
				(0.073)	(0.072)	(0.076)	(0.085)	(0.085)	(0.101)
Num.Obs	999	999	999	999	999	999	999	999	999
R^2	0.599	0.576	0.486	0.598	0.573	0.483	0.603	0.576	0.487
R^2 Adj	0.596	0.572	0.482	0.595	0.570	0.478	0.599	0.572	0.482
RMSE	1.11	1.14	1.29	1.11	1.14	1.30	1.10	1.14	1.29

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Acknowledgements The authors want to express their gratitude to Johanna Hölzl and Daria Szafran at University of Mannheim, and Jacob Beck at Ludwig-Maximilians-Universität München for setup and administration of the surveys.

Author contributions M.N. wrote the main manuscript text and conducted the statistical analyses. All authors engaged in scale development, interpretation of results, as well as review and editing of the manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL. This work has been partially funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under the National Research Data Infrastructure – NFDI 27/1 - 460037581 - BERD@NFDI.

Data availability All data generated or analyzed during this study can be made accessible. http://www.gesis.orgOur R code and analysis outputs are available on the Open Science Framework repository https://

osf.io/j36vd/ The two survey data sets are part of forthcoming publications of collaborating research teams, also referenced in the repository.

Declarations

Conflict of interest The authors declare no competing interests.

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