Computers in Human Behavior: Artificial Humans 3 (2025) 100106

Contents lists available at ScienceDirect

Computers in Human Behavior: Artificial Humans

journal homepage: www.journals.elsevier.com/computers-in-human-behavior-artificial-humans

An economical measure of attitudes towards artificial intelligence in work, healthcare, and education (ATTARI-WHE)☆

Timo Gnambs[a,*], Jan-Philipp Stein[b], Markus Appel[c], Florian Griese[d], Sabine Zinn[d,e]

[a] Leibniz Institute for Educational Trajectories, Bamberg, Germany
[b] Chemnitz University of Technology, Chemnitz, Germany
[c] University of Würzburg, Würzburg, Germany
[d] German Institute for Economic Research, Berlin, Germany
[e] Humboldt University Berlin, Berlin, Germany

ARTICLE INFO

Keywords:
Artificial intelligence
Attitudes
Work
Healthcare
Education
Social survey

ABSTRACT

Artificial intelligence (AI) has profoundly transformed numerous facets of both private and professional life. Understanding how people evaluate AI is crucial for predicting its future adoption and addressing potential barriers. However, existing instruments measuring attitudes towards AI often focus on specific technologies or cross-domain evaluations, while domain-specific measurement instruments are scarce. Therefore, this study introduces the nine-item *Attitudes towards Artificial Intelligence in Work, Healthcare, and Education* (ATTARI-WHE) scale. Using a diverse sample of $N = 1083$ respondents from Germany, the psychometric properties of the instrument were evaluated. The results demonstrated low rates of missing responses, minimal response biases, and a robust measurement model that was invariant across sex, age, education, and employment status. These findings support the use of the ATTARI-WHE to assess AI attitudes in the work, healthcare, and education domains, with three items each. Its brevity makes it particularly well-suited for use in social surveys, web-based studies, or longitudinal research where assessment time is limited.

1. Introduction

Artificial intelligence (AI) has become an integral part in many contexts of human life. By now, this fundamental transformation has not only changed the way people spend their leisure time (e.g., by guiding users' media and news exposure; Shin et al., 2022), but it also echoes throughout countless occupations and work environments, including the healthcare sector (Zahlan et al., 2023), education-related jobs (Giannakos et al., 2024), the service industry (Rather, 2024), research and development (Johnson et al., 2022), as well as manufacturing lines worldwide (Weichert et al., 2019). For the citizens in many regions worldwide, the on-going shift towards an AI-powered society certainly brings with it many opportunities—such as the cutting of tedious or dangerous human tasks, additional tools to acquire and share knowledge, novel forms of mobility, or even a more effective and robust healthcare system. At the same time, the rapid technological changes occurring all over the world also invoke severe risks and challenges (e.g., Kelly et al., 2023; Stein et al., 2019); for instance, individuals might lose their jobs to AI replacements or experience a devaluation of previously human-centered products and activities (such as artistry, caretaking, or interpersonal communication). Taken together, both positive and negative prospects of emergent AI technologies crucially affect people's attitudes towards them. In turn, the successful adoption of such innovations clearly hinges on a thorough understanding of how individuals make sense of AI, both in their daily life as well as the workplace.

To this end, scientific scholars have developed a growing number of instruments that measure AI-related attitudes either as a general, overarching construct (e.g., Wang & Wang, 2022) or as the quite narrow evaluation of specific technologies (e.g., Qu et al., 2021). Whereas a recent addition to this body of research, the *Attitude towards Artificial Intelligence* (ATTARI-12) scale by Stein and colleagues (2024), overcomes many conceptual and psychometric problems of other instruments, it measures AI attitudes entirely independent of specific

☆ We have no conflicts of interest to disclose. The study was not preregistered. The raw data will be released as part of the data distribution for the *German Socioeconomic Panel Study* (GSOEP Version 41). The analysis code and results are provided at https://osf.io/mgj5u.

* Corresponding author. Leibniz Institute for Educational Trajectories, Wilhelmsplatz 3, 96047, Bamberg, Germany.
E-mail address: timo.gnambs@lifbi.de (T. Gnambs).

https://doi.org/10.1016/j.chbah.2024.100106
Received 7 October 2024; Received in revised form 25 November 2024; Accepted 25 November 2024
Available online 28 November 2024

applications. For several purposes and use cases, this will likely provide an ideal level of abstraction; however, in other instances, assessments of AI-related attitudes could also benefit from a *domain-specific* approach, so as to help respondents think concretely, rather than abstractly, about AI in specific contexts (while still going beyond the narrow perspective on explicit technologies). Moreover, a 12-item instrument measuring a single construct, such as the ATTARI-12, appears quite lengthy for inclusion in large-scale social surveys or studies with repeated measurements. Therefore, we introduce an economical version of the previously established scale, offering three separate forms that focus on distinct and highly relevant fields of application (work, healthcare, education).

1.1. Attitudes towards AI and how to measure them

Attitudes are enduring psychological tendencies that reflect individuals' evaluations of certain objects, people, or concepts along a continuum with varying degrees of favor or disfavor (Eagly & Chaiken, 2007). These evaluations are shaped by direct experiences, such as personal interactions with an attitude object, and indirect experiences, such as those formed through observation or imagined contact. According to the tripartite model of attitudes (Rosenberg & Hovland, 1960), attitudes consist of three interrelated components. The *cognitive component* refers to beliefs, thoughts, and knowledge about the attitude object. It reflects cognitive assessments of perceived characteristics or associations regarding the target being evaluated. The *affective component* encompasses the emotions associated with the object, whether positive (e.g., joy) or negative (e.g., disgust). These emotional reactions often underpin how strongly someone feels about their attitude. Finally, the *behavioral component* includes actions, tendencies, or intentions toward the attitude object, reflecting how one might respond based on their evaluation. This integrative view assumes that attitudes are a general evaluative summary of an object derived from thoughts, emotions, and behaviors (Zanna & Rempel, 2008). The model represents a comprehensive framework for understanding how individuals evaluate their social and physical environments, which in turn shapes their future preferences, choices, and interactions.

Several attempts have been made to measure attitudes toward AI, often focusing on quite specific use cases and applications, such as driverless cars (Qu et al., 2021), skin cancer diagnostics with AI (Jutzi et al., 2020), or robots (Gnambs & Appel, 2019). A recent large-scale British study even explored the perceived risks and benefits across 17 AI use cases, including smart speakers, robotic vacuum cleaners, or autonomous weapons (Ada Lovelace Institute & The Alan Turing Institute, 2023). While useful, this approach has some limitations. Given the fast pace at which new AI technologies are being developed, comprehensively covering AI applications that are currently in use is rather impractical. Also, it is quite difficult to predict which technologies are here to stay and will be in use in the near future. Thus, for large-scale social surveys, instruments measuring attitudes towards AI independent of specific technologies—in terms of a more overarching attitude object—appear more promising.

Despite the need for general AI attitude scales, however, many of the instruments suggested for this purpose have conceptual and/or psychometric weaknesses. For example, some focus exclusively on negative impressions concerning AI, such as the *AI Anxiety Scale* (AIAS; Wang & Wang, 2022) and the *Threats to Artificial Intelligence Scale* (TAI; Kieslich et al., 2021), neglecting positive aspects of AI. Others, such as the *Attitudes Towards Artificial Intelligence Scale* (ATAI; Sindermann et al., 2021) and the *General Attitudes Towards Artificial Intelligence Scale* (GAAIS; Schepman & Rodway, 2023), capture both positive and negative aspects but fail to measure AI attitudes as a common construct across items. Moreover, some instruments combine general and domain-specific items, thus diluting the measured construct, or suffer from poor reliability (e.g., Sindermann et al., 2021).

In response to these limitations, Stein and colleagues (2024) developed the ATTARI-12 to measure general attitudes towards AI as an abstract concept. Drawing on the tripartite model of attitudes (Eagly & Chaiken, 2007; Zanna & Rempel, 2008), the ATTARI-12 measures general AI attitudes including their cognitive, affective, and behavioral facets, without referring to specific AI technologies or domains. Each facet includes two positively and two negatively phrased items to control for acquiescence bias. In a series of studies, the authors corroborated an essentially unidimensional measurement structure, high internal consistency of the total score (coefficient alpha ≈.90), strong test-retest reliability (r_{tt} = .80), and validity with regard to technological career aspirations, attitudes towards specific AI technologies, and personality traits.

While the ATTARI-12 is a theoretically sound and psychometrically robust instrument, its length may present a challenge, particularly for the measurement of a single construct in large-scale social surveys. In these situations, economic constraints and the need to minimize respondent burden often require shorter instruments (Rammstedt & Beierlein, 2014). This typically results in scales encompassing only three or two, sometimes even single-item measurements, despite repeated criticisms regarding their reliability and validity (see Allen et al., 2022, for a discussion). Importantly, attitudes toward AI may vary across domains. For example, individuals may have favorable views of AI in educational settings that support learning processes but exhibit skepticism toward AI-assisted medical diagnostics. Similar patterns have been previously reported for attitudes towards specific AI technologies (Gnambs & Appel, 2019). Although respondents reported rather positive attitudes towards robots in general, they indicated more positive attitudes towards robots in the workplace than in the context of healthcare. This highlights that attitudes towards the same object may vary between different application domains and may also depart from general evaluations of the same attitude object. Despite this fact, domain-specific AI attitude scales that measure generalized attitudes within particular fields of application, independent of specific technologies, are scarce. Those that exist were often developed ad-hoc, thus lacking rigorous psychometric evaluation. A notable exception is the work by Park and colleagues (2024), who developed a multifaceted instrument to measure AI attitudes in the workplace. Yet, with a total length of 25 items, the utility of the resulting scale for large-scale social studies may be limited.

A shorter, domain-specific adaptation of the ATTARI-12 might represent an important measurement tool for large-scale social surveys or longitudinal research where assessment times are costly. Such an instrument could measure general attitudes toward AI within specific domains, such as education and healthcare, to allow for meaningful comparative analyses across domains while retaining psychometric rigor.

1.2. Development of the ATTARI-WHE

The development of the new instrument was guided by four primary objectives. First, the instrument should allow for the measurement of attitudes towards AI, independent of specific technologies or applications. Second, the instrument needed to assess domain-specific attitudes toward AI across three key contexts: work, healthcare, and education. These domains were chosen because they not only represent areas in which diverse AI technologies already have a pronounced impact in practice (see the reviews by Kasneci et al., 2023; Martinez-Ortigosa et al., 2023; Pereira et al., 2023), but they are also relevant for a broad range of people, as most individuals have direct experience or personal stakes in at least one, if not all, of these domains. Third, the instrument should adhere to the tripartite model of attitudes (Eagly & Chaiken, 2007; Zanna & Rempel, 2008) to remain consistent with the structure of the original ATTARI-12 (Stein et al., 2024). Finally, the instrument should be designed as an efficient measure suitable for use in large-scale social surveys where interview time is typically limited.

To meet these goals, the domain-specific *Attitudes Towards Artificial Intelligence scale in Work, Healthcare, and Education* (ATTARI-WHE) scale was adapted from the ATTARI-12 (Stein et al., 2024). For each domain (work, healthcare, education), one positively worded item from each of the three attitudinal facets—cognitive, affective, and behavioral—was selected and rephrased to reflect the specific context (e.g., by adding the qualifier “at work”, “in medicine and healthcare”, or “for learning and teaching”). This resulted in a three-item scale for each domain that maintained the conceptual structure of the ATTARI-12. Given the need for brevity, negatively worded items were excluded to accommodate the interview time in social surveys. While negatively worded items in the ATTARI-12 serve primarily to control for acquiescence bias, Stein and colleagues (2024) posited that they do not capture qualitatively distinct attitudes. Therefore, their exclusion in the ATTARI-WHE does not compromise the instrument’s ability to measure attitudes but improves its efficiency and practicality in survey contexts. The resulting ATTARI-WHE provides a concise measure of domain-specific AI attitudes, with each subscale assessing the same attitudinal facets as the original ATTARI-12, but within the contexts of work, healthcare, and education.

2. The present study

The present study evaluated the psychometric properties of the ATTARI-WHE to assess its suitability for future large-scale social surveys. First, the distribution of missing values and response scales usage was examined to identify items that may be problematic for respondents. Next, confirmatory factor analyses scrutinized the hypothesized measurement structure and precision of the domain scores. Furthermore, measurement invariance across key sociodemographic characteristics was analyzed to demonstrate that the ATTARI-WHE measures AI attitudes comparably in diverse subgroups. Together these analyses provided insights into the psychometric properties of the ATTARI-WHE to understand its strengths and limitations for future research and practical application.

3. Materials and method

3.1. Sample and procedure

A quota sample of respondents was drawn from a German online panel that included individuals willing to participate in social research studies. The panel constituted a probability sample that is continually recruited using telephone interviews to cover the German population aged 18 or above. The present study aimed to recruit 700 employed participants (70%) and 300 participants currently out of the labor force (30%; e.g., retired, in education/training, unemployed). Because social surveys are often plagued with pronounced non-response rates (e.g., König et al., 2021), a gross sample of 4000 individuals were invited in May 2024 to participate in an unproctored web-based survey. Of these, 1084 took part in the study, resulting in a participation rate of 27%. One participant was excluded from the analyses because no valid responses were observed on the administered items, yielding 1083 participants. This final sample included 818 employed individuals (32% women) and 265 individuals out of the labor force (72% women). To evaluate whether the nonresponse was systematic, we compared gender, age, and employment distributions between the gross and net samples. Deviations were minor, with a maximum difference of 5%, suggesting the nonresponse was not systematic. The mean age of the respondents was 52.31 years ($SD = 12.01$), with the lower and upper quartile falling at 46 and 62 years, respectively. The average socioeconomic status of the sample was rather high as indicated by the large proportion of participants who had obtained school-leaving qualifications (64%) which enable access to higher education in Germany.

3.2. Instrument

The nine items included in the ATTARI-WHE were presented with five-point response scales, with response options ranging from 0 (strongly disagree) to 4 (strongly agree). Additionally, respondents could indicate that they felt unable or unwilling to respond to a specific item. To avoid sequence effects, the items of the ATTARI-WHE were presented in randomized order to each participant. While there was no time limit for answering the items, the average interview time for the entire instrument was 2 min. The items of the ATTARI-WHE, including an introductory definition of the AI concept, are provided in Appendix A.

The ATTARI-WHE permits the calculation of different scale scores, depending on the specific research objective. Firstly, three domain scores can be derived to measure attitudes towards AI in the context of work, healthcare, and education. Secondly, three facet scores can be calculated to measure the cognitive, affective, and behavioral attitude components. Finally, a total score across all items can be created to capture general attitudes towards AI, similar to the ATTARI-12. Items that respondents were either unwilling or unable to answer are treated as missing values and, thus, excluded in the calculation of the different scale scores.

3.3. Statistical analyses

The proportion of missing values for each item and the number of omitted responses for each person were analyzed to identify potential problems (e.g., unclear meaning, difficulties in understanding) with individual items or in subgroups of participants (e.g., older respondents). Then, three response styles were examined to ascertain whether the observed responses reflected non-differentiation (straight-lining), midpoint responding, or extreme responding. Non-differentiation represents responses that are (nearly) identical across different items and, thus, is a consequence of participants failing to differentiate between response alternatives (Kim et al., 2019). The probability of non-differentiation was calculated as $\sum p_i^2$, where p_i represents the proportion of responses with the value i across an item battery (Linville et al., 1986). The index was standardized to assume values between 0 and 100, with larger values indicating a greater degree of non-differentiation. Midpoint responding represents the disproportionate selection of the middle response category (“neither”) and was calculated for each respondent following Jacobs et al. (2020) as the percentage of midpoint responses. Finally, extreme responding represents a preference for the most extreme response categories (“strongly disagree” or “strongly agree”) and was calculated as the percentage of extreme responses for each participant (see Jacobs et al., 2020). Differences in response styles were compared between sociodemographic subgroups of respondents to identify individuals who might have experienced greater difficulties in expressing their attitudes using the ATTARI-WHE. Thresholds for practically relevant subgroup differences were derived from empirical effect size distributions in psychological research (Lovakov & Agadullina, 2021). We considered standardized mean differences exceeding Cohen’s $d = 0.15$ or 0.36 as small or medium effects, respectively.

The factor structure of the ATTARI-WHE was examined with confirmatory factor analyses using maximum likelihood estimation and the Yuan and Bentler (2000) test statistic. The fit of each model was evaluated using the robust root mean squared error of approximation (RMSEA; Brosseau-Liard et al., 2012), the standardized root mean square residual (SRMR), and the robust comparative fit index (CFI; Brosseau-Liard & Savalei, 2014). Following Schermelleh-Engel et al. (2003), we considered values of RMSEA $\leq$.05/.08, SRMR $\leq$.05/.10, and CFI $\geq$.97/.95 to represent a good/acceptable model fit. Five theory-driven models were examined for the ATTARI-WHE: Model 1 specified a single latent factor for all nine items, whereas Models 2 and 3 modeled three correlated latent factors, either for the three application domains (work, healthcare, education) or attitude facets (cognitive, affective, behavioral). Model 4 jointly modeled the domains and facets, thus, specifying six latent factors. Although the domain factors and the facet factors were permitted to correlate among each other, the domain factors were assumed to be uncorrelated with the facet factors. Finally, Model 5 specified a bifactor structure with a general factor for all nine items and four orthogonal method factors representing the healthcare and education domains as well as the affect and behavior facets. Following Eid and colleagues (2017), no specific factors were specified for the work domain and cognitive facet which therefore, served as the reference domain and facet. Graphical representations for these models are provided in Fig. S1 of the supplementary material. The latent factors in these models were identified by fixing the latent factor variances to 1. Given that scale scores for the ATTARI-WHE are calculated as means across items, thereby implicitly weighting each item equally, the examined factor models accounted for this by constraining the loadings on each factor (McNeish & Wolf, 2020).

Measurement invariance across sex, age, education, and employment status was studied using moderated factor analysis (Kolbe et al., 2024). To this end, the parameters of the best fitting factor model (Model 4) were conditioned on the moderators. Then, metric and scalar invariance was examined by evaluating the standardized regression weights of the moderators on the factor loadings or intercepts, respectively. As thresholds for practically relevant non-invariance, we considered standardized moderating effects on factor loadings below .10 as negligible, between .10 and .20 as small, between .20 and .30 as noteworthy, and above .30 as large and therefore potentially problematic for fair comparisons along the studied variable. Furthermore, standardized differences in intercepts were classified as small, medium, and large if they exceeded 0.25, 0.50, or 0.75, respectively. These thresholds correspond to typical differences often observed in empirical invariance studies (Nye et al., 2019).

The reliabilities of the different subscales were calculated as coefficient alpha and omega (Flora, 2020). In addition, the proportion of common variance explained by the latent factors was calculated to ascertain the extent to which the variance of the item scores is attributable to the measured constructs.

The analyses were conducted in *R* (R Core Team, 2024). Latent variable analyses were performed using *lavaan* (Version 0.6–18; Rosseel, 2012) and *OpenMx* (Boker et al., 2023). Descriptive analyses relied on *psych* (Revelle, 2024) and *MBESS* (Kelley, 2023), while plots were generated with *ggplot2* (Version 3.5.1; Wickham, 2016). General data handling was supported by *tidyr* (Wickham et al., 2024) and *dplyr* (Wickham et al., 2023).

The raw data will be released as part of the data distribution for the *German Socioeconomic Panel Study* (GSOEP Version 41).[1] Analysis code and results are available at https://osf.io/mgj5u/.

3.4. Ethics statement

This study was conducted in full compliance with the ethical standards outlined in the Declaration of Helsinki, as well as the principles set forth by the European Code of Conduct for Research Integrity. Additionally, it adheres to the requirements of the general data protection regulation in Germany to ensure the privacy and protection of all data collected and analyzed. All participants provided informed consent, and their rights, autonomy, and confidentiality were upheld throughout the research process.

4. Results

4.1. Omitted responses per item and person

The proportion of omitted responses per item ranged from 2.1% to 4.8% with a median value of 2.6% (see Table 1). The median omission rate for the items of the healthcare domain was 3.9%, which was slightly higher than the median rates observed for the work (2.4%) and education domains (2.7%). This suggests that some respondents experienced greater challenges in forming attitudes towards AI in healthcare than in the other domains. Also, items pertaining to the cognitive attitude facet exhibited a higher proportion of omitted responses (Mdn = 3.9%) compared to items pertaining to the affective or behavioral facet (each Mdn = 2.6%). The subgroup comparisons presented in Table S1 of the supplementary material revealed few systematic differences in missing rates between sexes (women, men), age groups (20–40 years, 41–60 years, 61–76 years), educational groups (with or without university entrance qualifications), or employment groups (full-time employed, part-time employed, out of the labor force). Although men, individuals with higher education, and those in full-time employment tended to exhibit less omitted responses, only few of these differences were significant at $p < .05$. The largest difference was observed for the cognitive attitude item in the education domain, which had significantly more omitted responses among the youngest respondents (8.8%) compared to middle-aged (4.3%) and older respondents (3.1%). Interestingly, this pattern was reversed in the work domain for which higher missing rates were observed for middle-aged (2.0%) or older respondents (3.1%) compared to younger respondents (1.0%). Also, individuals out of the labor force exhibited a significantly higher tendency to omit the behavioral item of the work domain (5.3%) compared to those who were employed (less than 2%). Regardless of these descriptive differences, the overall missing rates were not markedly elevated or systematically associated with respondent characteristics.

Most of the participants (84.8%) did not omit any response and answered all items of the ATTARI-WHE. In contrast, 6.6% and 2.7% of the sample, respectively, failed to provide a response to one or two items. The average number of omitted responses was significantly higher ($p < .05$) for the healthcare subscale ($M = 0.11$, $SD = 0.40$) than for the work ($M = 0.07$, $SD = 0.29$) or education ($M = 0.09$, $SD = 0.36$) subscales. Also, women had more omitted responses ($M = 0.33$, $SD = 0.22$) than men ($M = 0.22$, $SD = 0.74$); the respective effect size was rather small, Cohen's $d = -0.14$. The age of the respondents or their educational level had no effect on the number of omitted responses (see Table S2 of the online supplement). The results indicate that most participants had no difficulties with the administered instrument, although the healthcare subscale may have presented a slight challenge for some respondents. Furthermore, there was no substantial association between the tendency to omit responses and respondent characteristics.

4.2. Response scale usage

The items of the ATTARI-WHE were accompanied by five-point response scales. Descriptive analyses (see Fig. 1) demonstrated that for certain items the different response options were rather unequally used by the respondents. Notably, for items pertaining to the cognitive facet over two-thirds of the participants expressed (strong) agreement. However, a relatively small proportion of them expressed (strong) disagreement or had a neutral opinion. In contrast, the items pertaining to the affective and behavioral facets exhibited more balanced distributions of responses across the available response options.

Analysis of the three response style indicators revealed little non-differentiation and few cases of midpoint responding and of extreme responding (see Fig. S2 in the supplementary material). The median value of the standardized scale point variation was 44.5, indicating that most respondents selected different response options and did not engage in substantial straightlining. Similarly, the median percentage of midpoint or extreme responses was 22.2% and 0.0% respectively. If a threshold of 75 is adopted to distinguish careful respondents from careless responses, then approximately 12.6%, 0.9%, or 4.3% of the sample is classified as inattentive and probably low-fidelity participants. Using multiple criteria, for example, the scale point variation in combination with the percentage of extreme responses, resulted in the identification of 2.9% respondents with careless response behavior.

[1] https://www.diw.de/en/diw_01.c.601584.en/data_access.html.

Table 1
Means, standard deviations, missing rates, and factor loadings for ATTARI-WHE items.

Domain	Facet	M	SD	OR	r_{id}	r_{if}	r_{it}	λ_d	λ_f	λ_g
Work	Cognitive	2.85	0.82	2.12	.60	.61	.65	.71	.37	.79
	Affective	2.21	1.01	2.40	.63	.64	.68	.61	.50	.69
	Behavioral	2.03	1.07	2.40	.58	.61	.66	.58	.47	.64
Health-care	Cognitive	2.81	0.94	4.80	.72	.55	.67	.80	.33	.67
	Affective	2.39	1.06	2.59	.71	.63	.66	.70	.47	.62
	Behavioral	2.29	1.07	3.88	.65	.51	.61	.67	.46	.60
Edu-cation	Cognitive	2.54	0.98	3.88	.69	.50	.62	.72	.34	.69
	Affective	2.18	1.05	2.68	.62	.55	.63	.65	.47	.62
	Behavioral	2.24	1.08	2.59	.59	.60	.63	.64	.45	.59

Note. N = 1083. OR = Percentage of omitted responses. r_{id} = Corrected item-domain correlation; r_{if} = Corrected item-facet correlation; r_{it} = Corrected item-total correlation; λ_d/λ_f = Standardized loading on domain/facet factor in domain and facet model (Model 4 in Table 3); λ_g = Standardized loading on general factor in general factor model (Model 5 in Table 3).

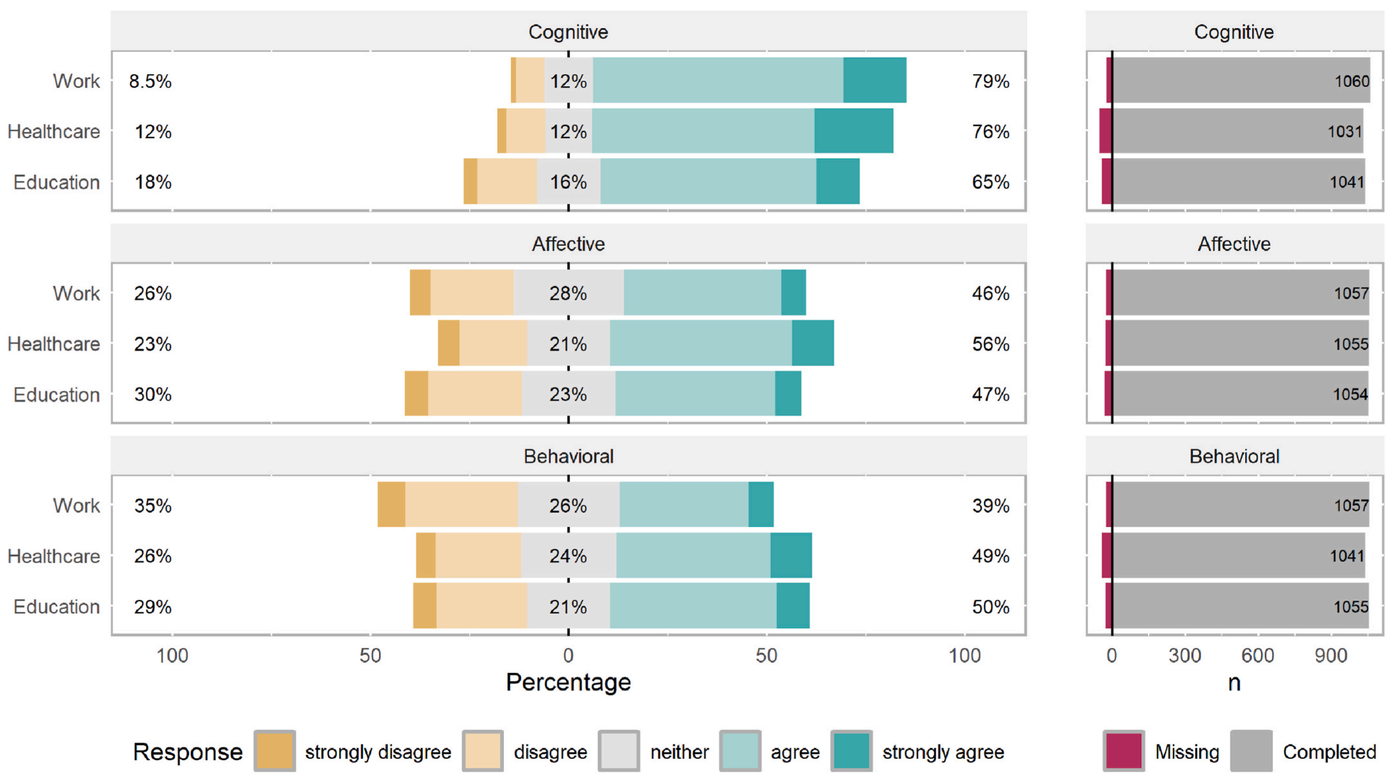

Fig. 1. Response distributions of ATTARI-WHE items.

Taken together, these results demonstrate that the responses to the ATTARI-WHE in the present sample were not unduly influenced by systematic response styles. Moreover, comparisons of the response style indicators between sexes, age groups, educational groups, and employment groups, as summarized in Tables S3–S5 of the supplement material, revealed only few notable differences depending on the sociodemographic characteristics of the respondents. The most pronounced effect was observed for the degree of non-differentiation, which increased with respondents' age, resulting in a medium-sized effect of Cohen's d = 0.29. The remaining effects were small to negligible.

4.3. *Evaluation of factor structure*

The corrected item-(sub)score correlations for the domain and facet subscales as well as the total score are reported in Table 1. The respective correlations for all items and (sub)scales were substantial, falling between .58 and .75. Furthermore, the three domain scores and the three facet scores did not exhibit unexpected high correlations (e.g., exceeding .90), which would suggest that they captured identical constructs (see Table 2). These results provide initial support for the hypothesized subscale structure.

The dimensionality of the ATTARI-WHE was evaluated more systematically by specifying five competing factor models. The fit statistics of the respective confirmatory factor analyses are presented in Table 3. The results demonstrate that the simple models which either specified a single latent factor for all items (Model 1) or three correlated factors for the domains or facets (Models 2 and 3) exhibited an inadequate fit. In contrast, the combined model, which acknowledged the domain and facet structure together, exhibited an excellent model fit, as indicated by an RMSEA of .05, a SRMS of .05, and a CFI of .99. Furthermore, the standardized loadings on the latent domain factors were substantial, ranging from .57 to .72 (Mdn = .65; see Table 1). Consequently, the latent domain factors for work, healthcare, and education explained approximately 66%, 75%, and 72% of the common item variance. In contrast, the standardized loadings on the three latent facet factors were smaller, though non-negligible, falling between .33 and .50 (Mdn = .46; see Table 1). Consequently, the factors for the cognitive, affective, and behavioral attitude facet explained a relatively modest proportion of the

Table 2
Means, standard deviations, reliabilities, and correlations of ATTARI-WHE scales.

Scale	*M*	*SD*	ECV	α	ω	Correlations					
						W	H	E	C	A	B
Work (W)	2.36	0.81	.66	.76	.77		.72	.79			
Healthcare (H)	2.48	0.90	.75	.83	.83	.64		.50			
Education (E)	2.31	0.87	.72	.78	.79	.69	.51				
Cognitive (C)	2.73	0.75	.18	.73	.73					.70	.55
Affective (A)	2.26	0.86	.35	.76	.76				.72		.60
Behavioral (B)	2.19	0.87	.35	.74	.75				.67	.68	
Total score	2.39	0.74	.67	.89	.89	.77†	.62†	.66†	.76†	.76†	.73†

Note. $N = 1083$. α/ω = Coefficient alpha/omega reliability. ECV = Explained common variance of items in subscale/total scale. † Corrected subscale-total correlation. Lower diagonal values represent manifest score correlations, while upper diagonal values represent latent factor correlations from domain and facet model (Model 4 in Table 3). Correlations between domain and facet scores are not meaningful because of mathematical coupling (i.e., shared items between subscales) and, thus, are not reported. All correlations are significant at $p < .05$.

Table 3
Model fit statistics for measurement models of the ATTARI-WHE

Model	χ^2 (*df*)	CFI	RMSEA	SRMR	AIC	BIC
1. Single factor model	647.89 (35)	.83	.15	.08	23258	23353
2. Domain model	254.42 (30)	.94	.09	.06	22789	22909
3. Facet model	607.74 (30)	.84	.15	.07	23200	23320
4. Domain and facet model	71.81 (24)	.99	.05	.03	22584	22734
5. General factor model	110.62 (31)	.98	.05	.05	22611	22726

Note. $N = 1083$. CFI = Comparative fit index, RMSEA = Root mean squared error of approximation, SRMR = Standardized root mean residual, AIC = Akaike information criterion, BIC = Bayesian information criterion. Visual representations of the models and factor loadings are given in Fig. S1 of the supplementary material.

common item variance, amounting to 18%, 35%, and 35%, respectively. The three latent domain factors were significantly ($p < .05$) correlated (see Table 2). While the work domain correlated with the healthcare and education domain at .79 and .72, respectively, the correlation between the healthcare and education domains was relatively weaker at .55. Similarly, the behavioral factor correlated with the cognitive and affective factors at .55 and .60, respectively. At the same time, the cognitive and affective factors demonstrated a stronger correlation of .70. These results corroborate the subscale structure of the ATTARI-WHE. Despite the latent domain and facet factors not being orthogonal, all correlations fell substantially below 1, indicating that they measured distinct constructs.

The bifactor model (Model 5 in Table 3) exhibited a similarly good fit as the oblique domain and facet model (Model 4). This result, along with the substantial latent factor correlations found for the latent domain factors, suggest that a general factor may also represent an adequate representation of the item responses. The respective factor loadings are reported in Table 1. The standardized loadings on the general factor were substantial, ranging from .58 to .79 (*Mdn* = .64). The general factor explained approximately 67% of the variance in the ATTARI-WHE items.

4.4. Reliability

Table 2 presents the internal consistencies of the subscale and total scores. Despite including only three items, the subscales demonstrated satisfactory reliabilities that fell between .73 and .83. The reliability of the total score was excellent at .89. Consequently, the ATTARI-WHE allows measuring domain and facet scores as well as a general attitude score with considerable precision.

4.5. Evaluation of measurement invariance

The measurement model of the ATTARI-WHE, as defined in the correlated domain and facet model (Model 4), was compared across various sociodemographic groups to evaluate the comparability of scale scores across these variables. The results of the respective analyses are presented in Table 4. They demonstrate that the factor loadings were highly robust across sex, age, education, and employment status. The only exception was the loading on the cognitive facet factor which was found to be significantly ($p < .05$) smaller for individuals in part-time employment in comparison to those in full-time employment. With a standardized difference of −0.33, the respective effect was rather large. In contrast, none of the other factor loadings demonstrated any notable degree of invariance. Although 8 of the 45 moderating effects on the intercepts were significant, the respective sizes of all standardized differences were negligible, falling between −0.20 and 0.21 and thus not of practical relevance. These findings suggest that the ATTARI-WHE exhibited a relatively stable measurement model, allowing valid comparisons of attitude scores between the examined sociodemographic groups.

5. Discussion

AI is no longer at the fringe of daily life, but has become a sizeable factor across multiple domains, including work, healthcare, and education. This development is associated with a public discussion of the opportunities and challenges of AI in many societies worldwide. Understanding what people think (and how they feel) about AI has become increasingly important, as attitudes are well-established predictors of technology adoption (Marikyan et al., 2023). Despite the growing importance of AI, there has been a lack of well-validated instruments to measure attitudes toward AI within different domains. Therefore, the current research aimed to develop brief, psychometrically robust scales that assess AI attitudes in work, healthcare, and education. The findings from this study provided strong support for the viability of the ATTARI-WHE. The instrument demonstrated minimal susceptibility to response biases, exhibited strong reliability, and revealed a stable measurement model across different demographic groups that supported the calculation of different subscale scores. Together, these results show that the ATTARI-WHE is a sound instrument to assess AI attitudes in different domains within about 2 minutes, particularly in situations when efficiency is paramount such as in large-scale social surveys.

5.1. Suggested use of the ATTARI-WHE

The ATTARI-WHE is suited for research that focuses on AI as a generalizable (yet context-dependent) concept rather than on specific, current AI technologies. Particularly, whenever attitudes are expected to

Table 4
Differences in factor loadings and intercepts by sociodemographic groups.

Factor/Item	Women	10 years of age	Higher education	Part-time employment	No employment
Difference in factor loadings					
Work	−.03	.03	−.09	−.01	.06
	(−.04)	(.03)	(−.11)	(−.01)	(.07)
Healthcare	−.06	.01	−.01	−.02	.00
	(−.06)	(.01)	(−.01)	(−.02)	(.00)
Education	.05	.02	−.02	−.05	.02
	(.05)	(.02)	(−.02)	(−.06)	(.02)
Cognitive	.08	.06	−.08	−.27	.03
	(.10)	(.08)	(−.10)	(−.33)*	(.04)
Affective	−.02	−.03	.08	−.06	−.04
	(−.02)	(−.03)	(.08)	(−.06)	(−.04)
Behavioral	.10	.02	.03	−.15	−.05
	(.10)	(.02)	(.03)	(−.16)	(−.05)
Difference in intercepts					
Work: cognitive	−0.04	−0.07	0.18	−0.07	0.04
	(−0.05)	(−0.08)[a]	(0.21)[a]	(−0.09)	(0.04)
Work: affective	0.02	−0.07	0.06	−0.07	−0.04
	(0.02)	(−0.07)[a]	(0.06)	(−0.06)	(−0.04)
Work: behavioral	−0.10	−0.03	0.13	−0.10	0.00
	(−0.10)	(−0.03)	(0.12)	(−0.09)	(0.00)
Healthcare: cognitive	0.00	−0.07	0.12	−0.04	−0.01
	(0.00)	(−0.07)[a]	(0.12)	(−0.04)	(−0.01)
Healthcare: affective	0.02	−0.05	0.05	−0.05	−0.03
	(0.02)	(−0.05)	(0.05)	(−0.05)	(−0.03)
Healthcare: behavioral	−0.05	−0.03	0.07	−0.13	−0.03
	(−0.04)	(−0.03)	(0.07)	(−0.12)	(−0.02)
Education: cognitive	−0.16	−0.04	0.10	0.04	0.10
	(−0.17)[a]	(−0.04)	(0.10)	(0.04)	(0.11)
Education: affective	−0.21	0.00	0.14	−0.03	0.03
	(−0.20)[a]	(0.00)	(0.13)[a]	(−0.03)	(0.03)
Education: behavioral	−0.14	0.04	0.16	−0.03	−0.10
	(−0.14)	(0.04)	(0.15)[a]	(−0.03)	(−0.09)

Note. $N = 1049$, Reported are unstandardized results with standardized results in parenthesis. Reference group are men at the mean age of the sample (52 years) with lower education and full-time employment. Results are based on the domain and facet model (Model 4 in Table 3). Because factor loadings were constrained for each factor, a single difference in factor loadings is reported.
[a] $p < .05$ with adjustments for multiple comparisons (Benjamini & Hochberg, 1995).

differ across different domains, the ATTARI-WHE is preferable over the ATTARI-12 (Stein et al., 2024), which assesses AI attitudes independent of the technology's field of use. Similarly, practitioners and scholars focusing on only one of the three included domains might appreciate the possibility to apply only the respective subscale of the ATTARI-WHE for their work—an approach that we would deem to be conceptually feasible.

While the ATTARI-WHE also allows for the calculation of a total score across all three subscales to capture general AI attitudes, such a score would still be based on the three chosen focal domains (work, healthcare, education). Therefore, if truly domain-independent attitudes are of interest, the ATTARI-12 would be the recommended choice. Although the ATTRI-WHE can also yield separate scores for the cognitive, affective, and behavioral components of attitudes, we recommend against using these subscale scores. Contemporary models of attitude emphasize the importance of considering these components together to capture the full breadth of an individual's evaluation of an attitude object (Eagly & Chaiken, 2007). If substantial acquiescence biases are expected, the limitation to positively worded items might distort responses to the ATTARI-WHE to some degree. Although respective biases were negligible in the present study, researchers anticipating higher levels of acquiescence may choose to extend the instrument to an 18-item version by incorporating negatively phrased items. Respective items along with preliminary quality assessments of the longer scale are provided in the supplementary material. The decision to extend the scale should however carefully weigh the trade-off between addressing potential acquiescence effects and the advantage of the current instrument's brevity. We also acknowledge that the provision of "don't know" response options in attitude surveys remains a topic of active debate. While some authors argue against their use because they tend to increase satisficing (e.g., Krosnick et al., 2002), others believe that they help filter out respondents with non-attitudes (e.g., Elkjær & Wlezien, 2024). Depending on the researchers' perspective, it may therefore be appropriate to consider omitting an explicit "don't know" option in certain applications.

5.2. Limitations and directions for future research

Although the present research thoroughly evaluated the psychometric properties of the ATTARI-WHE, several limitations need to be noted that open opportunities for follow-up research. First, the domains covered by the instrument – work, healthcare, and education – were chosen due to the strong influx of AI technologies in these domains, affecting broad segments of the population (e.g., Kasneci et al., 2023; Martinez-Ortigosa et al., 2023; Pereira et al., 2023). Still, these are certainly not the only areas AI already plays an important role or is likely to become important in the near future. Therefore, the ATTARI-WHE could be extended to address additional domains such as finances (e.g., robo-advisors and -brokers), transportation (e.g., autonomous vehicles), or entertainment (e.g., AI in gaming and film production). Second, the presented analyses focused on the internal structure of the instrument to demonstrate the quality of the measurement model. Further studies are encouraged to also provide evidence regarding its predictive validity to explain real-world outcomes such as the adoption for specific AI technologies in work, healthcare, and education. Third, measurement precision was limited to analyses of internal consistency. Additional information on the dependability, that is, test-retest reliability, could provide deeper insights into the psychometric functioning of the instrument. Finally, the instrument was only evaluated in a German-speaking sample. Although an English version is available (see

Appendix), the generalizability of the findings to other language versions and cultural contexts remains an open agenda for follow-up studies.

6. Conclusion

The present study offered strong evidence supporting the ATTARI-WHE as a psychometrically sound instrument for assessing attitudes toward AI in work, healthcare, and education. With a total of only nine items (three items per domain) and an interview time of about 2 min, the scale demonstrated high reliability and measurement invariance across key demographic groups, making it efficient and posing little burden on respondents. Its brevity makes it particularly suitable for use in large-scale social surveys, web-based studies, and longitudinal research, where time constraints often limit the number of items that can be administered to each participant. In sum, we believe that the ATTARI-WHE fills an important gap in AI research by providing a reliable means of measuring attitudes across contexts, thereby facilitating deeper insights into public perceptions and aiding in the broader investigation of AI's societal impact.

CRediT authorship contribution statement

Timo Gnambs: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Jan-Philipp Stein:** Writing – review & editing, Writing – original draft. **Markus Appel:** Writing – review & editing. **Florian Griese:** Writing – review & editing, Investigation, Data curation. **Sabine Zinn:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbah.2024.100106.

Appendix B. Attitudes Towards Artificial Intelligence in Work, Healthcare, and Education Scale (ATTARI-WHE)

Definition		
We would like to know your opinion on artificial intelligence. Artificial intelligence refers to technical devices that can perform tasks that typically require human intelligence. It enables machines to sense, act, and adapt autonomously. Artificial intelligence can be part of a computer program or an online application, but can also be found in various machines such as robots. It can be used in the workplace, in medicine and nursing as well as in education and training.		
Instruction		
Please indicate your level of agreement for each statement. There are no correct or incorrect answers.		
Domain	**Facet**	**Item**
Work	Cognitive	Artificial intelligence offers good solutions for many job tasks.
	Affective	I have a good feeling when I think about the use of artificial intelligence in daily working life.
	Behavioral[2]	If I have to complete an important task at work, I would rather choose a technology with artificial intelligence than one without.
Healthcare	Cognitive	Artificial intelligence offers good solutions in medicine and nursing.
	Affective	I have a good feeling when I think about how artificial intelligence is being used in healthcare and nursing.
	Behavioral	For the treatment of a serious illness, I would rather choose a technology with artificial intelligence than one without.
Education	Cognitive	Artificial intelligence is helpful for learning and teaching.
	Affective	I have positive feelings when I think about how artificial intelligence is used in education and training.
	Behavioral	If I want to learn something new, I would choose a learning program with artificial intelligence rather than one without.
Response format		
0 = strongly disagree, 1 = disagree, 2 = neither, 3 = agree, 4 = strongly agree −1 = cannot or do not want to answer		

[2] For future use, we recommend rephrasing the behavioral, work item and using the subjunctive (i.e., "If I had to …") to better address non-employed persons.

The items should be presented in randomized order to avoid sequence effects. Subscale scores and overall scale scores are created by calculating the mean across the three item scores for each domain/facet or the mean across all nine item scores. Response scores of −1 are treated as omitted responses and are excluded from the calculation of the (sub)scale scores. Scores should only be calculated for respondents with valid responses to at least half of the items.

The German version of the ATTARI-WHE is provided in the supplementary material.

References

Ada Lovelace Institute & The Alan Turing Institute. (2023). *How do people feel about AI? A nationally representative survey of public attitudes to artificial intelligence in Britain.* https://adalovelaceinstitute.org/report/public-attitudes-ai.

Allen, M. S., Iliescu, D., & Greiff, S. (2022). Single item measures in psychological science. *European Journal of Psychological Assessment, 28*(1), 1–5. https://doi.org/10.1027/1015-5759/a000699

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B, 57*, 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Boker, S.M., Neale, M.C., Maes, H.H., Spiegel, M., Brick, T.R., Estabrook, R., … Kirkpatrick, R.M. (2023). *OpenMx: Extended structural equation modelling* (Version 2.21.11) [Computer software]. doi:10.32614/CRAN.package.OpenMx.

Brosseau-Liard, P. E., & Savalei, V. (2014). Adjusting relative fit indices for nonnormality. *Multivariate Behavioral Research, 49*, 460–470. https://doi.org/10.1080/00273171.2014.933697

Brosseau-Liard, P., Savalei, V., & Li, L. (2012). An investigation of the sample performance of two non-normality corrections for RMSEA. *Multivariate Behavioral Research, 47*, 904–930. https://doi.org/10.1080/00273171.2012.715252

Eagly, A. H., & Chaiken, S. (2007). The advantages of an inclusive definition of attitude. *Social Cognition, 25*(5), 582–602. https://doi.org/10.1521/soco.2007.25.5.582

Eid, M., Geiser, C., Koch, T., & Heene, M. (2017). Anomalous results in G-factor models: Explanations and alternatives. *Psychological Methods, 22*, 541–562. https://doi.org/10.1037/met0000083

Elkjær, M. A., & Wlezien, C. (2024). *Estimating public opinion from surveys: The impact of including a "don't know" response option in policy preference questions. Political science research and methods*. Advance online publication. https://doi.org/10.1017/psrm.2024.42

Flora, D. B. (2020). Your coefficient alpha is probably wrong, but which coefficient omega is right? A tutorial on using R to obtain better reliability estimates. *Advances in Methods and Practices in Psychological Science, 3*(4), 484–501. https://doi.org/10.1177/2515245920951747

Giannakos, M., Azevedo, R., Brusilovsky, P., Cukurova, M., Dimitriadis, Y., Hernandez-Leo, D., Järvelä, S., Mavrikis, M., & Rienties, B. (2024). *The promise and challenges of generative AI in education. Behaviour and Information Technology*. Advance online publication. https://doi.org/10.1080/0144929x.2024.2394886

Gnambs, T., & Appel, M. (2019). Are robots becoming unpopular? Changes in attitudes towards autonomous robotic systems in Europe. *Computers in Human Behavior, 93*, 53–61. https://doi.org/10.1016/j.chb.2018.11.045

Jacobs, L., Loosveldt, G., & Beullens, K. (2020). Do interviewer assessments of respondents' performance accurately reflect response behavior? *Field Methods, 32*, 193–212. https://doi.org/10.1177/1525822x19888616

Johnson, P. C., Laurell, C., Ots, M., & Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development – automation or augmentation, exploration or exploitation? *Technological Forecasting and Social Change, 179*, Article 121636. https://doi.org/10.1016/j.techfore.2022.121636

Jutzi, T. B., Krieghoff-Henning, E. I., Holland-Letz, T., Utikal, J. S., Hauschild, A., Schadendorf, D., & Brinker, T. J. (2020). Artificial intelligence in skin cancer diagnostics: The patients' perspective. *Frontiers of Medicine, 7*, 233. https://doi.org/10.3389/fmed.2020.00233

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kelley, K. (2023). *MBESS: The MBESS R package* (Version 4.9.3) [Computer software]. . https://doi.org/10.32614/CRAN.package.MBESS

Kelly, S., Kaye, S., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics, 77*, Article 101925. https://doi.org/10.1016/j.tele.2022.101925

Kieslich, K., Lünich, M., & Marcinkowski, F. (2021). The Threats of artificial intelligence scale (TAI): Development, measurement and test over three application domains. *International Journal of Social Robotics, 13*, 1563–1577. https://doi.org/10.1007/s12369-020-00734-w

Kim, Y., Dykema, J., Stevenson, J., Black, P., & Moberg, D. P. (2019). Straightlining: Overview of measurement, comparison of indicators, and effects in mail-web mixed-mode surveys. *Social Science Computer Review, 27*, 214–233. https://doi.org/10.1177/0894439317752406

Kolbe, L., Molenaar, D., Jak, S., & Jorgensen, T. D. (2024). Assessing measurement invariance with moderated nonlinear factor analysis sing the R package OpenMx. *Psychological Methods, 29*, 388–406. https://doi.org/10.1037/met0000501

König, C., Sakshaug, J. W., Stegmaier, J., & Kohaut, S. (2021). Trends in establishment survey nonresponse rates and nonresponse bias: Evidence from the 2001-2017 IAB establishment panel. *Journal of Official Statistics, 37*(4), 931–953. https://doi.org/10.2478/jos-2021-0040

Krosnick, J. A., Holbrook, A. L., Berent, M. K., Carson, R. T., Michael Hanemann, W., Kopp, R. J., & Conaway, M. (2002). The impact of" no opinion" response options on data quality: Non-attitude reduction or an invitation to satisfice? *Public Opinion Quarterly, 66*(3), 371–403. https://doi.org/10.1086/341394

Linville, P. W., Salovey, P., & Fischer, G. W. (1986). Stereotyping and perceived distributions of social characteristics: An application to ingroup outgroup perception. In J. F. Dovidio, & S. L. Gaertner (Eds.), *Prejudice, discrimination, and racism* (pp. 165–208). Academic Press.

Lovakov, A., & Agadullina, E. R. (2021). Empirically derived guidelines for effect size interpretation in social psychology. *European Journal of Social Psychology, 51*(3), 485–504. https://doi.org/10.1002/ejsp.2752

Martinez-Ortigosa, A., Martinez-Granados, A., Gil-Hernández, E., Rodriguez-Arrastia, M., Ropero-Padilla, C., & Roman, P. (2023). Applications of artificial intelligence in nursing care: A systematic review. *Journal of Nursing Management, 2023*, Article 3219127. https://doi.org/10.1155/2023/3219127

McNeish, D., & Wolf, M. G. (2020). Thinking twice about sum scores. *Behavior Research Methods, 52*, 2287–2305. https://doi.org/10.3758/s13428-020-01398-0

Nye, C. D., Bradburn, J., Olenick, J., Bialko, C., & Drasgow, F. (2019). How big are my effects? Examining the magnitude of effect sizes in studies of measurement equivalence. *Organizational Research Methods, 22*(3), 678–709. https://doi.org/10.1177/1094428118761122

Park, J., Woo, S. E., & Kim, J. (2024). Attitudes towards artificial intelligence at work: Scale development and validation. *Journal of Occupational and Organizational Psychology, 97*(3), 920–951. https://doi.org/10.1111/joop.12502

Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review, 33*(1), Article 100857. https://doi.org/10.1016/j.hrmr.2021.100857

Qu, W., Sun, H., & Ge, Y. (2021). The effects of trait anxiety and the big five personality traits on self-driving car acceptance. *Transportation, 48*, 2663–2679. https://doi.org/10.1007/s11116-020-10143-7

R Core Team. *R: A language and environment for statistical computing* (Version 4.4.1) [Computer software]. Austria: R Foundation for Statistical Computing. https://www.R-project.org.

Rammstedt, B., & Beierlein, C. (2014). Can't we make it any shorter? *Journal of Individual Differences, 35*(4), 212–220. https://doi.org/10.1027/1614-0001/a000141

Rather, R. A. (2024). AI-Powered ChatGPT in the hospitality and tourism industry: Benefits, challenges, theoretical framework, propositions and future research directions. *Tourism Recreation Research. Advance online publication*. https://doi.org/10.1080/02508281.2023.2287799

Revelle, W. (2024). *psych: Procedures for psychological, psychometric, and personality research (Version 2.4.6) [Computer software]*. Northwestern University. https://doi.org/10.32614/CRAN.package.psych.

Rosenberg, M. J., & Hovland, C. I. (1960). Cognitive, affective, and behavioral components of attitudes. In C. I. Hovland, & M. J. Rosenberg (Eds.), *Attitude organization and change: An analysis of consistency among attitude components* (pp. 1–14). Yale University Press.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Schepman, A., & Rodway, P. (2023). The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory validation and associations with personality, corporate distrust, and general trust. *International Journal of Human-Computer Interaction, 39* (13), 2724–2741. https://doi.org/10.1080/10447318.2022.2085400

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research, 8*(2), 23–74. https://doi.org/10.23668/psycharchives.12784

Shin, D., Hameleers, M., Park, Y. J., Kim, J. N., Trielli, D., Diakopoulos, N., Helberger, N., Lewis, S. C., Westlund, O., & Baumann, S. (2022). Countering algorithmic bias and disinformation and effectively harnessing the power of AI in media. *Journalism & Mass Communication Quarterly, 99*(4), 887–907. https://doi.org/10.1177/10776990221129245

Sindermann, C., Sha, P., Zhou, M., Wernicke, J., Schmitt, H. S., Li, M., & Montag, C. (2021). Assessing the attitude towards artificial intelligence: Introduction of a short measure German, Chinese, and English language. *Künstliche Intelligenz, 35*, 109–118. https://doi.org/10.1007/s13218-020-00689-0

Stein, J.-P., Liebold, B., & Ohler, P. (2019). Stay back, clever thing! Linking situational control and human uniqueness concerns to the aversion against autonomous technology. *Computers in Human Behavior, 95*, 73–82. https://doi.org/10.1016/j.chb.2019.01.021

Stein, J.-P., Messingschlager, T., Gnambs, T., Hutmacher, F., & Appel, M. (2024). Attitudes towards AI: Measurement and associations with personality. *Scientific Reports, 14*, 2909. https://doi.org/10.1038/s41598-024-53335-2

Wang, Y. Y., & Wang, Y. S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments, 30*, 619–634. https://doi.org/10.1080/10494820.2019.1674887

Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., & Wrobel, S. (2019). A review of machine learning for the optimization of production processes. *The International Journal of Advanced Manufacturing Technology, 104*(5–8), 1889–1902. https://doi.org/10.1007/s00170-019-03988-5

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer.

Marikyan, D., Papagiannidis, S., & Stewart, G. (2023). Technology acceptance research: Meta-analysis. *Journal of Information Science*. https://doi.org/10.1177/01655515231191177. Advance online publication.

Wickham, H., François, R., Henry, L., Müller, K., & Vaughan, D. (2023). *dplyr: A grammar of data manipulation* (Version 1.1.4) [Computer software]. . https://doi.org/10.32614/CRAN.package.dplyr

Wickham, H., Vaughan, D., & Girlich, M. (2024). *tidyr: Tidy messy data* (Version 1.3.1) [Computer software]. . https://doi.org/10.32614/CRAN.package.tidyr

Yuan, K. H., & Bentler, P. M. (2000). Three likelihood-based methods for mean and covariance structure analysis with non-normal missing data. *Sociological Methodology, 30*(1), 165–200. https://doi.org/10.1111/0081-1750.00078

Zahlan, A., Ranjan, R. P., & Hayes, D. (2023). Artificial intelligence innovation in healthcare: Literature review, exploratory analysis, and future research. *Technology in Society, 74*, Article 102321. https://doi.org/10.1016/j.techsoc.2023.102321

Zanna, M. P., & Rempel, J. K. (2008). Attitudes: A new look at an old concept. In R. H. Fazio, & R. E. Petty (Eds.), *Attitudes: Their structure, function, and consequences* (pp. 7–15). Psychology Press.