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A Scoping Review of Psychometric Scales Assessing Attitudes Toward Artificial Intelligence

Огляд психометричних шкал з оцінки ставлення до штучного інтелекту

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Abstract

The purpose of this article is to explore human attitude toward artificial intelligence (AI) in the context of its rapid development and growing presence in everyday life. Given the widespread adoption of AI technologies, there is an increasing need in accurate and valid instruments for assessing attitudes. The author examines validated psychometric tools designed to evaluate human attitude toward AI, which are of interest for psychologists and sociologists, as well as for researchers and developers of AI technologies. As reflected in the title, the aim of this scoping review is identification and systematization of existing scales created to assess attitude toward artificial intelligence using modern standardized protocols. The analysis covers five validated instruments: GAAIS, ATTARI-12, ATAI, AIAS-4, and AIAI.

Research methods. The current review was conducted following PRISMA-ScR methodology and quality evaluation criteria adopted by the author from the COSMIN and the Standards for Educational and Psychological Testing.

Results. The article discusses theoretical foundations and structural design of these tools, along with empirical evidence of their scientific rigor. A detailed analysis of the psychometric properties and practical implications of each scale is provided, including reliability, validity, and reporting transparency. Limitation discovered was the lack of cross-cultural adaptation, as most scales were developed for Western countries and demonstrated limited applicability to other sociocultural populations. Findings indicated that ATTARI-12 received the highest scores across most criteria, including test-retest reliability. The other four scales showed strong internal consistency and validity, but at the same time they demonstrated certain limitations in terms of their cross-cultural adaptation, sample representativeness, and temporal stability.

Conclusions. The article concluded that while there are several high-quality validated psychometric instruments, future research should focus on their standardization, temporal stability, and cross-cultural validation. The review also highlighted the need to develop specialized tools for evaluating attitudes toward emerging forms of AI, including generative AI (e.g., ChatGPT, Claude, Gemini), as it rapidly gains popularity among users of different age, professional experience, and levels of digital competence.

Keywords: artificial intelligence, attitude toward AI, psychometric scales, validity, cross-cultural adaptation, ChatGPT, generative AI.

Анотація

Мета статті - дослідити ставлення людини до штучного інтелекту (ШІ) в контексті його стрімкого розвитку та зростаючої ролі у повсякденному житті. Зважаючи на поширення технологій ШІ, виникає потреба у точних та науково доказових інструментах для вимірювання ставлення. Автор розглядає валідизовані психометричні інструменти, призначені для оцінки ставлення людей до ШІ, що становлять інтерес для психологів, соціологів, а також для дослідників і розробників штучного інтелекту. Як випливає з назви статті, представлене дослідження має на меті ідентифікувати та систематизувати існуючі шкали оцінки ставлення до штучного інтелекту за допомогою сучасних стандартизованих протоколів. Аналіз охопив п’ять валідизованих інструментів: GAAIS, ATTARI-12, ATAI, AIAS-4 та AIAI.

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Методи дослідження. Для проведення оглядового дослідження були використані метод PRISMA-ScR та адаптовані автором критерії оцінки якості шкал, такі як COSMIN та Standards for Educational and Psychological Testing.

Результати. У статті розглянуті теоретичні засади створення цих шкал, їх структура, а також емпіричні підтвердження їх наукової доказовості. Також дається розгорнутий аналіз психометричних властивостей цих п’яти інструментів та їх прикладне значення. Докладно описані та оцінені критерії надійності, валідності та прозорості звітування. Зазначено недоліки виявлених шкал у зв’язку з їх недостатньою крос-культурною адаптацією, через розробку переважно для використання у західних країнах і недостатню пристосованість до інших мовних та соціокультурних середовищ. Результати дослідження показали, що шкала ATTARI-12 отримала найвищу оцінку за більшістю критеріїв, включаючи тест-ретест надійність. Чотири інші шкали мали високі показники внутрішньої узгодженості та підтверджену валідність, але при цьому мали певні обмеження щодо крос-культурної адаптації, репрезентативності та стабільності результатів у часі.

Висновки. Показано, що попри наявність якісних валідизованих психометричних інструментів, подальші дослідження мають зосередитися на їх стандартизації, перевірці стабільності результатів у часі та в інших культурних середовищах. Також наголошено на потребі розробки спеціалізованих інструментів для оцінки ставлення до нових видів штучного інтелекту, зокрема генеративного (наприклад, ChatGPT, Claude, Gemini), зважаючи на його зростаючу популярність серед користувачів різного віку, професійного досвіду та рівня цифрової компетентності.

Ключові слова: штучний інтелект, ставлення до ШІ, психометричні шкали, валідність, крос-культурна адаптація, ChatGPT, генеративний ШІ.

Rationale. In recent years, artificial intelligence (AI) has been on the rise, and it now plays a significant role in everyday routine and has a great transformative potential to change how we live (Kelley et al., 2021). According to

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Makridakis (2017) and Vesnic-Alujevic et al. (2020), global society will be heavily influenced by the AI within the next several decades. Notably, some researchers claim that AI integration will lead to downsizing of human jobs (Waytz & Norton, 2014), while others state that AI will replace some professions and generate new employment opportunities (Wilson et al., 2017). At the same time, in accordance with Haque (2022), generative AI tools like ChatGPT will partially replace "white-collar" employees due to their ability to analyze data, write and translate texts. In addition, introduction of text-creating and image-creating AI instruments has led to various concerns, including academic fraud and artistic authorship (Thorp, 2023). Moreover, further AI development can lead to negative impact on interpersonal relationships, fewer jobs, and human extinction (Gherhes, 2019).

Given these implications and further integration of AI into daily lives, many ethical, political, economic, and other implications of its use remain in question, and people are often hesitant to interact with AI software (McKee et al., 2023). Public acceptance of AI technologies and their adoption across various industries are heavily influenced by beliefs, feelings, and behavioral intentions toward artificial intelligence, and thus it has become critical to evaluate how people approach human-AI collaboration (Scantamburlo et al., 2023). Public perception of AI programs varies from optimism based on AI's ability to solve complex problems and conduct deep research and analysis to fear of reduced human control and algorithmic bias (Guingrich & Graziano, 2024). Consequently, close evaluation of attitudes toward artificial intelligence has emerged as a critical area in contemporary research, and this scoping review aims to systematically identify and analyze existing psychometric instruments that measure such attitudes.

By training their AI systems on large-scale datasets, leading technology companies have equipped these systems with an ability to process natural language, recognize objects with the help of computer vision, interact with environment via robotics, which helped AI rapidly acquire human-like capabilities (Xu et al., 2021; Liehner et al., 2023). Therefore, there is a significant interest in artificial intelligence across disciplines, which is reflected in the growing academic output:

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as of May 2025, PubMed lists 299,262 results for "artificial intelligence", ScienceDirect shows 380,109 results, and Google Scholar displays 7,570,000 results. Despite the growing number of publications on both AI and human attitude toward AI (Montag & Ali, 2025), there has been limited examination of existing psychometric scales assessing attitude toward artificial intelligence. This lack of studies complicates the process of selecting appropriate measurement tools, comparing findings of the studies, and identifying areas for further scale development and refinement. To address this gap, the present scoping review follows PRISMA-ScR guidelines to synthesize diverse methodologies and theoretical frameworks, prioritizing breadth over depth (Tricco et al., 2018).

Objectives. The scoping review aims to systematically identify and grade psychometric scales that assess attitude toward artificial intelligence; describe their characteristics (e.g. target populations, theoretical foundations, etc.); critically evaluate psychometric properties of these instruments (e.g. test-retest, internal consistency), their validity (e.g. construct, discriminant) and cultural adaptation; highlight gaps in existing measurement approaches.

Methods

Protocol. The protocol for this scoping review was developed a priori in April 2025 in accordance with Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews developed by Tricco et al. (2018). This protocol was developed primarily by the author in the consultation with the supervisor and other colleagues. The current protocol was not registered in a public repository such as Open Science Framework due to existing internal constraints of the project and its preliminary component of a broader PhD program.

To the best of our knowledge, this is the first scoping review aiming to comprehensively identify and categorize psychometric scales that assess attitudes toward artificial intelligence within the psychological research context. Although several reviews have investigated and compared existing frameworks (e.g. Montag

& Ali, 2025; Hering et al., 2024), none have been found that provide an overall overview or comparative analysis of the existing scales.

Eligibility Criteria. The rationale for choosing specific criteria was to ensure that we comprehensively cover existing and validated scales measuring attitude toward AI across diverse populations. We included both peer-reviewed journal articles, preliminary reports and other non-peer-reviewed studies published in English in the period of 2020-2024 that focused on assessing attitude toward artificial intelligence specifically. Such studies had to present original scale development methodologies and such scales needed to be validated across general population samples.

At the same time, we excluded studies that were not published in English or before 2020 and those that presented psychometric instruments measuring attitude toward technology or human-robot interaction. We also excluded studies that did not present unique scales and/or did not report on development, adaptation, and validation of the scales. Conference abstracts and dissertation publications were not included in this scoping review. Scales developed for assessing attitude toward AI in clinical or specialized populations and scales with single-item measures were excluded as well to ensure review of generalizable measurement scales only.

Information Sources. The search strategy was designed to find all relevant publications across platforms and manually select those that met the eligibility criteria with filtering publication dates to 2020-2025. We conducted the primary research across PsycINFO, PubMed/MEDLINE, Web of Science, Scopus, and Google Scholar as our aim was to ensure comprehensive coverage of interdisciplinary literature related to artificial intelligence and measuring attitude toward it, and according to Bosman et al. (2006), these databases would allow capturing various publications. We performed searches once a week between April and May 2025 to make sure that we include newly published studies in our review.

In our search we used various terms and keyword combinations related to scales measuring attitude toward AI, such as “AI”, “artificial intelligence”, “scale”, “questionnaire”, “attitude”, “perception”, “acceptance” using Boolean operators.

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Our search strings included ("AI" OR "artificial intelligence") AND ("scale" OR "measurement") AND ("attitude" OR "acceptance" OR "perception"). Our search combinations used for Google Scholar included "scales measuring attitude toward artificial intelligence", "scales measuring attitude toward AI", "scales assessing attitude toward AI", "scales measuring perception of AI", "scales measuring acceptance of AI". To ensure consistency in search execution, it was conducted independently by the author himself.

Use of Artificial Intelligence in Research Process. In addition to traditional database search, we utilized Perplexity Pro AI to search for potentially relevant publications. The search strategy for Perplexity AI was using the prompt "find all publications on scales measuring attitude (acceptance, perception, etc.) toward AI" and enabling the Pro mode, which can be chosen to ensure in-depth research and finding more relevant sources (Perplexity, n.d.). However, Perplexity Pro did not identify additional studies beyond those that we found previously using traditional database search. All critical research decisions were made independently by the author without AI assistance.

Selection of Sources of Evidence. The author conducted the screening process independently and no other parties were involved. The screening process involved initial screening of the title with further full-text review of potentially eligible publications as suggested by Pham et al. (2014). The author developed a standardized decision-making checklist to ensure systematic and consistent selection of studies.

The selection process included initial exclusion of the studies with titles that mentioned specific sample populations or adaptation of existing scales to specific countries or industries. Screening was performed without use of software as the volume of publications was manageable. Only five studies met all inclusion criteria.

Data Charting Process. As the primary goal was to ensure comprehensive and systematic extraction of data, we developed a data extraction form in Microsoft Excel that included key study characteristics and psychometric data needed for a comparative analysis of the scales measuring attitude toward AI. When charting

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data, we extracted study characteristics and divided them into seven groups: study characteristics, scale development, scale structure and content, psychometric properties, application context, practical considerations, and limitations.

The author manually extracted data over the period of one week and reviewed each study individually and iteratively. To ensure accuracy and consistency, the author used the original extraction template in Microsoft Excel. All information has been double-checked after the initial extraction and no cases of missing critical data were encountered; therefore, no contact with the authors of original publications was necessary. If certain minor or non-critical information was missing, it was marked as "not fully reported", and corresponding suggestions were later added to the recommendations section.

Data Items. To address the research objectives, we systematically collected relevant information from existing scales that evaluate attitude toward AI based on the methodological recommendations for scale development and evaluation suggested by DeVellis (2012) and Boateng (2018). We recorded data items and categorized them into seven categories, such as study characteristics, scale development, scale structure and content, psychometric properties, application context, practical considerations, and limitations, which together form a framework comparable to that described by Kyriazos et al. (2018).

Study characteristics included author names, year of publication, countries, design, samples, recruitment methods. Scale development data captured theoretical frameworks that were used, refinement, and construct definition. Scale structure and content information incorporated the number of items, dimensional structure, subscales (if any), facets represented, and response format. We have also methodically collected such psychometric properties as reliability, validity, and test-retest. Application context covered target population, cultural context, existing translations, and suitability. We also covered practical considerations including accessibility and implementation requirements. Finally, we charted limitations, such as cultural adaptation and measurement gaps.

Critical Appraisal. Given the emerging nature of AI attitude measurement with five scales currently available to assess general attitude toward artificial intelligence, we needed to utilize standardized methods to evaluate methodological rigor of the scales and adequacy of psychometric evidence. As no standardized appraisal tool evaluating attitude toward AI exists, we adapted certain criteria from the Standards for educational and psychological testing (AERA, APA & NCME, 2014) and from the COSMIN (COnsensus-based Standards for the selection of health Measurement INstruments) methodology (Mokkink et al., 2016).

For example, we used test development and revision standards, cultural adaptation adequacy criteria and evidence-based validity framework from the Standards for educational and psychological testing (AERA, APA & NCME, 2014) and reliability, validity, responsiveness, along with the systematic quality assessment criteria from the COSMIN (Mokkink et al., 2024). Combining these elements ensured quality-based scale categorization and evaluation, evidence-based recommendations, and grounded conclusions.

Synthesis of Results. We grouped the studies individually by the scales they introduced. First, we summarized theoretical foundations, psychometric properties, and other data items within each scale group. Second, we synthesized theoretical and conceptual evidence to identify convergent and divergent approaches utilized to assess attitude toward AI. Third, we conducted a systematic comparative analysis of various psychometric data. Fourth, we used methodological synthesis to evaluate scale development processes and validation approaches. Fifth, we examined cross-cultural and contextual evidence along with translation procedures. As the scales assessing attitude toward artificial intelligence were based on different theoretical frameworks, we used a narrative synthesis approach to identify patterns and gaps while comparing the scales to evaluate their psychometric adequacy. Evidence was presented mainly through narrative synthesis and comprehensive comparison tables with data extracted across the scales.

Results

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Selection of Sources of Evidence. As a result of a systematic and comprehensive research, the author managed to identify five psychometrically validated instruments. The scales were selected through multiple stages of screening and evaluation as initial search across platforms and databases yielded a substantial number of potentially relevant sources. The selection process completed by the author resulted in choosing five scales for this scoping review:

1) General Attitudes towards Artificial Intelligence Scale (GAAIS) developed by Schepman & Rodway (2022), a 20-item, 2-factor instrument that was validated across multiple UK samples (N=604 total);

2) Attitudes Towards AI and Robotics Index (ATTARI-12) by Stein et al. (2024), a 12-item, 1-dimension scale with validation across US and German populations (N=938 total);

3) Attitude Towards Artificial Intelligence (ATAI) designed by Sindermann et al. (2020), a 5-item, 2-factor scale validated across UK, German and Chinese samples (N=958 total);

4) AI Attitude Scale (AIAS-4) developed by Grassini (2023), a 4-item, 1-dimension brief tool validated across UK and US populations (N=530 total); and

5) Artificial Intelligence Attitudes Inventory (AIAI) by Krägeloh et al. (2024), a 16-item, 2-factor scale validated in US population (N=604 total), the only study that has not undergone peer review.

As the aim of this scoping review is to identify and compare psychometric instruments that measure general attitude toward AI and have proper validation and sample sizes, many other studies using similar psychometric instruments were excluded. We also excluded publications presenting tools to measure AI attitudes in specific industries, lacking adequate psychometric validation (although AIAI has not undergone peer review, the study was validated using Rasch methodology).

The final selection represents studies that were published between 2020-2024, which shows that new systematic AI attitude measurement tools recently appeared in psychological research. It also reflects this field's rapid development and growing scholarly interest in AI technologies.

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Characteristics of Sources of Evidence. The five studies we selected present different methodological approaches and encompass 3634 participants across UK, US, German, and Chinese populations. GAAIS, ATAI and AIAS-4 utilized a combination of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), AIAI used Item Response Theory (IRT) methodology and Rasch analysis, and ATTARI-12 was based on EFA/CFA and a bifactor S-1 modeling approach.

General Attitudes towards Artificial Intelligence Scale (GAAIS) by Schepman & Rodway (2022) measured positive and negative attitudes toward AI as separate constructs. Schepman & Rodway (2022) introduced a 20-item instrument and a two-study design where Study 1 (N=304) confirmed the two-factor structure and Study 2 (N=300) examined correlation between personality traits and attitude. This scale had good internal consistency (α=0.82-0.88 in Study 1; α=0.82-0.85 in Study 2) and was validated across the UK sample. GAAIS measured positive attitude toward AI by examining whether the population believed in beneficial application of AI and positive outcomes of its workplace integration, positively perceived economic opportunities that artificial intelligence could potentially provide, and eagerly waited for AI development. The scale also measured negative attitudes, including fear of AI, privacy and ethical issues, personal harm, and error-making concerns (Schepman & Rodway, 2022).

Attitudes Towards AI and Robotics Index (ATTARI-12) by Stein et al. (2024) incorporated cognitive, affective, and behavioral attitude facets presented in 12 items. The research designed included Study 1 (N=490, US MTurk) with initial validation, Study 2 (N=150) with test-retest reliability assessment among German students, and Study 3 (N=298) that analyzed personality predictors. The scale demonstrated high internal consistency (α=0.92-0.93) and a 4-5-week test-retest reliability (r=0.80, 26-36 days) (Stein et al., 2024). ATTARI-12 measured three groups of facets: cognitive (beliefs about AI's impact, its societal benefits and problem-solving capabilities), affective (excitement, fear, comfort and other emotional responses toward AI), and behavioral (intentions to use AI, preference of artificial intelligence vs. services provided by humans).

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Attitude Towards Artificial Intelligence (ATAI) by Sindermann et al. (2020) included a 5-item scale that measured acceptance and fear of artificial intelligence across German (N=461), Chinese (N=413) and UK (N=84) populations. This scale was developed on the basis of media debate in Germany and existing robot attitude scales, presumably Negative Attitude Towards Robots Scale created by Nomura et al. (2006) and Frankenstein Syndrome Questionnaire by Nomura et al. (2012). The internal consistency of this model is comparatively low (α=0.65-0.73 for acceptance of AI and α=0.61-0.66 for the fear of AI). ATAI evaluated acceptance of AI, including trust in AI and beliefs in the beneficial role of AI for the humanity, and fears of AI, including concerns that AI would replace humans at workplace, fear to use AI and to beliefs that artificial intelligence will destroy humankind (Sindermann et al., 2020).

AI Attitude Scale (AIAS-4) by Grassini (2023) presented a short AI attitude measure with 4 items and a one-dimension structure. The research design included Study 1 (N=230) that comprised of exploratory factor analysis across UK population and Study 2 (N=300) with the confirmatory validation of the results among the US population. This scale achieved high internal consistency (α=0.89-0.902). AIAS-4 assessed beliefs in overall positive role of AI, future intentions to use AI, beliefs in personal life and workplace improvements (Grassini, 2023).

Artificial Intelligence Attitude Inventory (AIAI) by Krägeloh et al. (2024) was the most sophisticated among the 5 scales reviewed as it utilized modern Rasch analysis and included 16 items with two separate 8-item subscales for positive and negative attitudes toward AI (8 positive + 8 negative = 16 in total). The authors initially tried a traditional factor analysis approach but later switched to IRT/Rasch methodology. Internal consistency reached was rather high (α=0.91-0.93). In detail, AIAI measured trust in decisions made by AI, improving human capabilities and healthcare, and social benefits; it also assessed concerns related to AI’s manipulation, harm to humanity, loss of human connection, unethical use of AI, and privacy concerns (Krägeloh et al., 2024).

Theoretical Foundations and Research Findings. General Attitudes towards Artificial Intelligence Scale (GAAIS) by Schepman & Rodway (2022) examines positive and negative attitudes toward artificial intelligence as bidimensional constructs and distinct psychological systems that can exist simultaneously. Presumably, GAAIS was influenced by Technology Acceptance Model by Davis (1989), which tried to explain and predict successful implementation of technology by understanding its acceptance (Marikyan & Papagiannidis, 2024). The authors also grounded GAAIS on automation trust theories and algorithm appreciation theory findings like those of Logg et al. (2019).

The key findings showed that introverts' attitude toward AI was more positive, most likely because of their preference to reduce social interaction (Schepman & Rodway, 2022). Also, authors showed that people with higher levels of agreeableness tended to have a forgiving attitude toward negative aspects of AI, and people with higher corporate distrust had negative AI attitude.

Attitudes Towards AI and Robotics Index (ATTARI-12) by Stein et al. (2024) was mainly an AI-adapted model of a classical tripartite attitude theory by Rosenberg & Hovland (1960) as it reviewed cognitive beliefs, affective responses, and behavioral intentions. The novelty of ATTARI-12 also included a combination of the Big Five personality theory, the Dark Triad, and technology acceptance theoretical frameworks.

The research showed that people with higher levels of agreeableness and trust had a more favorable attitude toward AI (Stein et al., 2024). Importantly, older individuals and people with a conspiracy mentality had negative attitude toward artificial intelligence.

Attitude Towards Artificial Intelligence (ATAI) by Sindermann et al. (2020) was based on existing robot attitude scales, such as Negative Attitude towards Robots Scale (NARS) developed by Nomura et al. (2006) and Frankenstein Syndrome Questionnaire (FSQ) presented by Nomura et al. (2012). The main concept of Sindermann et al. (2020) was that there exists a fundamental tension between acceptance and fear of artificial intelligence. Although NARS and FSQ focused on assessing attitude toward humanoid robots, they also used similar items and categories, including future social influences (vs. AI will destroy/benefit humankind in ATAI) and general attitudes (vs. AI fear/trust in ATAI) (Syrdal et al., 2009).

The key findings demonstrated that Chinese population had higher acceptance of AI and lowest fear of losing jobs to AI in comparison to samples from Germany and UK (Sindermann et al., 2020). Also, findings revealed that males have more interest in AI and a more positive attitude toward it.

AI Attitude Scale (AIAS-4) by Grassini (2023) mainly utilized the Technology Acceptance Model (and its concept of perceived usefulness) developed by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (and its concept of behavioral intention) by Venkatesh et al. (2003).

Key findings showed that gender was the only significant predictor and females appeared to have a lower level of AI acceptance than males; at the same time, age and education level were not statistically significant predictors (Grassini, 2023).

Artificial Intelligence Attitude Inventory (AIAI) by Krägeloh et al. (2024) utilized 44 items from NARS and FSQ questionnaires and used Rasch methodology to analyze categorical data. No other theories were explicitly mentioned.

The key findings demonstrated that White participants had significantly stronger negative views of AI than Black participants (Krägeloh et al., 2024). Neither positive nor negative attitudes were impacted by the region of residence; level of education did not have any significant effect on negative attitude toward artificial intelligence.

Critical Appraisal within Sources of Evidence. We critically appraised all five sources using a simplified framework based on COSMIN methodology (which was originally created for health measures) and Standards for Educational and Psychological Testing. We evaluated each study across five domains and rated them as Poor (insufficient evidence), Fair (limited evidence), Good (solid evidence), or

Excellent (comprehensive evidence). The results of this critical appraisal are summarized in Table 1 below.

Table 1

Critical Appraisal

Domain	GAAIS (Schepman & Rodway, 2022)	ATTARI-12 (Stein et al., 2024)	ATAI (Sindermann et al., 2020)	AIAS-4 (Grassini, 2023)	AIAI (Krägeloh et al., 2024)
Study Design and Methodology Quality	Good	Excellent	Good	Good	Excellent
Assessment Reliability	Good	Excellent	Fair	Good	Excellent
Validity Evidence	Good	Excellent	Good	Good	Good
Cultural and Contextual Validation	Fair	Good	Excellent	Good	Fair
Reporting Quality and Transparency	Excellent	Excellent	Good	Good	Excellent
Overall	Good	Excellent	Good	Good	Good

GAAIS by Schepman & Rodway (2022) received a good score overall, but its cultural and contextual validation was only Fair because there was no cross-cultural validation conducted and the study was limited to UK cultural context. *ATAI by Sindermann et al. (2020)* also received a good score, but its reliability assessment was Fair due to moderate internal consistency (Acceptance of AI α=0.65-0.73, Fear of AI α=0.61-0.66) and lack of test-retest reliability. *AIAS-4 by Grassini (2023)* received Good ratings for validity evidence as the scale is rather brief and thus lacks comprehensive validity assessment, but it had solid cultural validation. AIAI by Krägeloh et al. (2024) was ranked Good overall, but its cultural and contextual validation was also Fair as the study was limited to US context only.

It should be noted that *ATTARI-12 by Stein et al. (2024)* was the only source that was rated Excellent overall as it demonstrated a three-study design, the highest

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quality of validity evidence, an outstanding internal consistency (α=0.92-0.93), and test-retest reliability. At the same time, no study was evaluated with a Poor rating across all five domains, which reflects good overall quality of the studies selected for this scoping review.

Results of Individual Sources of Evidence. The extracted data were categorized into seven groups and are presented in corresponding tables (Tables 2-8):

Table 2
Study Characteristics

Study Characteristics	GAAIS	ATTARI-12	ATAI	AIAS-4	AIAI
Authors	Schepman, Rodway	Stein, Messingschla-ger, Gnambs, Hutmacher, Appel	Sindermann, Sha, Zhou, Wernicke, Schmitt, Li, Sariyska, Stavrou, Becker, Montag	Grassini	Krägeloh, Melekhov, Alyami, Medvedev
Year	2022 (confirmatory study; original scale developed in 2020)	2024	2020	2023	2024
Sample Countries	UK	Germany, USA	Germany, China, UK	UK, USA	USA
Study Design	Two-study cross-sectional validation	Multi-study validation with personality predictors	Cross-sectional multi-cultural validation	Two-study cross-sectional validation	Single cross-sectional with Rasch analysis
Sample Sizes	Study 1: N=304, Study 2: N=300	Study 1: N=490, Study 2: N=150, Study 3: N=298	Study 1: Germany (N=461), China (N=413), UK (N=84)	Study 1: N=230, Study 2: N=300	Study 1: N=604
Recruitment Methods	Prolific (UK)	MTurk (USA), German university students	University students (research projects), online convenienc	Prolific (UK and USA)	Qualtrics (USA)

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Table 3

Scale Development

Development Aspect	GAAIS	ATTARI-12	ATAI	AIAS-4	AIAI
Theoretical Frameworks	Trust theories, algorithm appreciation	Attitude trichotomy (cognitive, affective, behavioral), Big Five personality theory, Dark Triad	Media debates, robot attitude scales (NARS, FSQ)	Technology Acceptance Model (TAM), UTAUT	Robot attitude scales (NARS, FSQ) adapted for AI
Refinement Process	EFA→CFA with factor reduction (32→30 items)	Iterative development, bifactor analysis	Translation/ back-translation, cross-cultural adaptation, PCA validation	EFA with factor reduction (5→4 items)	Iterative Rasch analysis (96→16 items)
Construct Definition	Positive and negative attitudes as separate constructs	Unidimensional general attitude with multiple facets	Acceptance vs. Fear as bipolar constructs	Unidimensional general attitude toward AI utility	Positive and negative attitudes

Table 4

Scale Structure and Content

Characteristics	GAAIS	ATTARI-12	ATAI	AIAS-4	AIAI
Number of Items	20	12	5	4	16 (8+8)
Dimensional Structure	2-factor	1-factor	2-factor	1-factor	2-factor
Subscales	Positive (12 items), Negative (8 items)	Single unidimensional scale	Acceptance (2 items), Fear (3 items)	Single scale	Positive (8 items), negative (8 items)
Facets Represented	Utility, emotions, concerns, trust, control	Cognitive beliefs, affective responses, behavioral intentions	Trust, benefits, fears, job impact	Personal/ work benefits, future use, humanity impact	Benefits, concerns, trust, privacy, control
Response Format	5-point Likert	5-point Likert	11-point Likert (0-10)	10-point Likert (1-10)	5-point Likert

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Table 5
Psychometric Properties

Property	GAAIS	ATTARI-12	ATAI	AIAS-4	AIAI
Reliability (α)	α=0.82-0.88 in Study 1; α=0.82-0.85 in Study 2	0.92-0.93	Acceptance: 0.65-0.73, Fear: 0.61-0.66	α=0.89-0.902	Positive: 0.93, Negative: 0.91
Test-retest	Not assessed	r=0.804 (4-5 weeks)	Not assessed	Not assessed	Not assessed
Validity Evidence	CFA confirmed convergent validity with Technology Readiness Index	CFA confirmed convergent validity with voice assistants/robots	CFA confirmed convergent validity with willingness to use specific AI products	CFA confirmed convergent validity with AI career aspirations and technology attitudes	Rasch analysis confirmed separate positive/negative dimensions

Table 6
Application Context

Aspect	GAAIS	ATTARI-12	ATAI	AIAS-4	AIAI
Target Population	General adult population	General adults, students	General adults, students	General adult population	General adult population
Cultural Context	UK	Western (USA, Germany)	Multi-cultural (Western + East Asian)	Western (UK, USA)	USA
Existing Translations	English only	English, German	German, Chinese, English	English only	English only
Practical applications	Public opinion research, policy assessment, corporate trust research	Public opinion research, personality-based prediction of AI acceptance	Cross-cultural AI attitude research, brief public opinion research	Quick screening for AI attitudes, large-scale survey research	High-precision evaluation of AI attitude, detailed attitude profiling

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Table 7

Practical Considerations

Aspect	GAAIS	ATTARI-12	ATAI	AIAS-4	AIAI
Accessibility	Moderate length, standard format	Moderate length, balanced content	Very brief	Very brief	Longer but comprehensive
Implementation Requirements	Standard platforms, attention checks needed	Standard platforms, optional personality measures	Multi-language capability	Standard platforms, minimal requirements	Rasch analysis expertise

Table 8

Limitations

Limitation	GAAIS	ATTARI-12	ATAI	AIAS-4	AIAI
Cultural Adaptation	Limited to UK/Western context	Limited validation (USA and Germany)	Good cross-cultural base but limited scope	Western-centric, limited diversity (UK and USA)	USA only, needs cultural adaptation
Measurement Gaps	May miss emerging AI applications	May miss domain-specific attitudes	Brief format limits assessment depth	Very brief, may miss dimensions	Comprehensive but requires specialized analysis

These tables systematically present data items we extracted when overviewing the sources, and this allowed a comprehensive comparison of the scales measuring attitude toward artificial intelligence. The tables were made in accordance with PRISMA-ScR recommendations for presenting data in a structured format with a slight visual adaptation.

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Synthesis of Results. Systematic Identification and Grading of AI Attitude Scales. We have identified five psychometrically validated scales that were published between 2020-2024 and measured attitude toward artificial intelligence. We conducted critical appraising and ATTARI-12 was the only scale that received an excellent rating due to comprehensive validation, high reliability, test-retest assessment while four other scales (GAAIS, ATAI, AIAS-4, AIAI) received good quality ratings. No scales received poor ratings, which indicated reasonable methodology used by the researchers.

Description of Scale Characteristics. All scales have been thoroughly characterized and compared in accordance with PRISMA-ScR recommendations (Tricco et al., 2018). ATTARI-12 incorporated cognitive, affective, and behavioral facets, AIAS-4 focused on evaluating general AI utility, and GAAIS measured positive and negative attitudes as separate constructs, ATAI and AIAI incorporated and adapted certain elements from existing robot attitude theories. All five scales targeted general adult population and no scale aimed at professional or clinical populations.

Critical Evaluation of Psychometric Properties. It appeared that only ATTARI-12 possessed test-retest reliability and only ATAI provided comprehensive cross-cultural validation. GAAIS, ATTARI-12, AIAS-4 and AIAI showed high internal consistency while ATAI demonstrated certain issues (Acceptance α=0.65-0.73, Fear α=0.61-0.66). At the same time, all scales had solid construct validity as it was supported through factor analysis.

Gaps in Existing Measurement Approaches. Future development should consider certain gaps that were found when conducting comparative analysis of the scales. Future researchers should prioritize test-retest reliability and cross-cultural validation and ensure sufficient testing among various demographic groups (age, gender, education, profession, etc.).

Discussion

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Summary of evidence. This scoping review identified and graded five scales that represent important advances in AI attitude measurement. As they all were published between 2020 and 2024, we can conclude that this is a rapidly emerging field in psychological research, and we can expect development of new scales assessing AI attitude and perception in the nearest future. Notably, four out of five scales showed some methodological limitations, which indicates a need for a more comprehensive validation and cross-cultural adaptation. Among the scales, ATTARI-12 offered rigorous measurement, including test-retest reliability. However, researchers should work on longer-term validation and take the cultural context and research objectives into account when selecting an appropriate scale for further investigation.

Limitations. This scoping review has multiple limitations, which should be acknowledged. A single-reviewer approach represents a first limitation of this study. Second, we searched for English-language publications only while there could potentially be high-quality scales assessing attitude toward AI published in other languages. Third, given the recency of the performed research, the instruments identified lacked long-term validation. Finally, domain- or industry-specific scales could provide important insights but were initially excluded from the search.

Conclusions. This scoping review represents the first comprehensive examination of validated scales that measure general public attitudes toward AI and bring methodological innovations to light. Although scales demonstrated adequate psychometric properties, they also had certain gaps, such as limited cross-cultural validation and insufficient temporal stability, as four out of five scales had not been evaluated for test-retest reliability.

Future priorities include removing such limitations, incorporating standardized validation protocols, and developing scales that evaluate attitude toward specific AI domains, such as Large Language Models (LLMs), Multimodal AI, Generative AI, and AI agents. Equally important is a need to develop scales accessing AI attitude among professional populations and non-Western populations. With the rapid expansion of AI technologies into daily lives, measurement

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approaches and instruments must evolve and adapt accordingly to capture public attitudes toward artificial intelligence.

Contemporary AI tools play a significant role in numerous industries as they evolved from general-purpose tools to specialized instruments aimed at serving specific groups of people across domains (Akhand et al., 2024). With the rise of conversational AI (e.g., ChatGPT, Claude, Gemini), measurement approaches must transform as well to capture attitude toward artificial intelligence among people from different cultures, domains, socioeconomic and educational backgrounds. According to Williams & Lim (2024), artificial intelligence substantially impacts how people think, feel, and behave, and with constant development of AI tools, methodological approaches should transform as well. This defines the direction of further psychological research as artificial intelligence is playing a growing role in our lives and everyday task completion (Renkema & Tursunbayeva, 2024). In our rapidly changing environment, the development of culturally adapted and industry-specific measurement instruments will be essential to understand and optimize human-AI interaction.

Conflict of Interests. The author declares no conflict of interest.

Use of Artificial Intelligence. AI assistance was used to locate recent publications on the scales assessing attitudes toward AI. All theoretical interpretations, critical analysis, findings synthesis and conclusions were developed independently by the author.

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