Questionnaires and Scales on Human–Artificial Intelligence Interaction: Where Are We Now?

Hansen LI[1], Lunxin CHEN[2], Hengzhi DENG[3], Zhengyang MEI[4], Qingqing LI[4], Yike LI[4] and Xing ZHANG[5]

[1]School of Physical Education, Sichuan Agricultural University, Ya'an 625014, China
[2]School of Physical Education and Sports, Central China Normal University, Wuhan 430079, China
[3]Faculty of Sports and Exercise Science, University of Malaya, Kuala Lumpur 50603, Malaysia
[4]College of Physical Education, Southwest University, Chongqing 400715, China
[5]Department of Physical Education and Sport, Faculty of Sport Sciences, University of Granada, Granada 18071, Spain
* Corresponding author: Hansen Li (hanson-swu@foxmail.com)

Abstract: With the rise of large language models such as ChatGPT, human–artificial intelligence (AI) interaction has become a major research focus, prompting the development of numerous measurement tools. This study examined the current landscape of AI-related behavioral and psychological instruments through bibliometric analysis and narrative review. A systematic search of Web of Science and Scopus identified 115 papers. Results showed a rapid increase in studies since 2022, with China as the leading contributor, although collaboration among scholars, institutions, and countries remained limited. Attitudes toward AI and AI literacy were the most frequently studied constructs. Narrative analysis identified 13 categories of instruments, including anxiety and fear of AI, dependence and problematic use, self-efficacy, trust, and user experience. Among them, the General Attitudes towards Artificial Intelligence Scale, Artificial Intelligence Literacy Scale, and Artificial Intelligence Anxiety Scale were the most widely used. Overall, these findings provide an overview of the field, support future tool selection, and highlight the need for greater attention to questionnaire translation, terminology, and conceptual clarity.

Keywords: Artificial intelligence, large language models, natural language learning, human–computer interaction

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1. Introduction

Artificial intelligence (AI) is a complex concept, and no universally accepted definition exists to date (Sheikh et al., 2023). Existing descriptions include "a general system capable of simulating human thought and taking adaptive actions in real-world environments" (Sun et al., 2024), or "the tangible real-world capability of non-human machines or artificial entities to perform, task solve, communicate, interact, and act logically as it occurs with biological humans" (Gil de Zúñiga et al., 2024). For the public, AI often refers to machines that can solve problems like humans, appearing in forms such as personal assistants (Siri, Alexa, Google Assistant), automated public transportation, aviation, and computer games (Mintz & Brodie, 2019).

Although the study of AI has a long history, tracing back to a 1956 academic conference (Xu et al., 2021), it only recently entered the mainstream public sphere. This change was largely driven by the launch of ChatGPT. ChatGPT, short for Chat Generative Pre-Trained Transformer, is a large language model developed by OpenAI. Its ability to process complex language comprehension and generation tasks in conversational form significantly lowered the threshold of AI use and drew global attention (Wu et al., 2023). Within five days of release, ChatGPT attracted one million users, and the number quickly grew to two million within two weeks (Kim, 2023). This phenomenon further spurred the development of other AI chatbots, such as Bing Chat and Deepseek, which is popular in the Chinese market.

Riding the wave of ChatGPT, AI has been transforming industries worldwide (Kamalov et al., 2023) and is regarded as a key force of the Fourth Industrial Revolution (Javaid et al., 2023; Mhlanga, 2022). AI-generated text, images, and video content are becoming increasingly prevalent (Anantrasirichai & Bull, 2022). Against this backdrop, human–AI interaction has emerged as a central topic within human–computer interaction research. How do people use AI, and what behavioral, psychological, and health-related impacts does AI bring? These questions have sparked extensive exploration. For instance, a preliminary investigation suggests that people's social backgrounds and other characteristics are related to the use of AI chatbots (Li et al., 2026). Some studies found that AI adoption significantly increases work stress and burnout (Kim & Lee, 2024). Others suggested that excessive ChatGPT use may pose addiction risks (Kooli et al., 2025; Lin & Chien, 2024). Similar findings were also reported in terms of AI dependency (Zhang et al., 2025a; Zhang et al., 2025b). However, most of these studies are still at an early stage and require deeper investigation.

Further quantitative research on these sociological issues and phenomena must be grounded in scientific and reliable measurement tools. As a result, many scholars have devoted efforts to developing AI-related scales and questionnaires, such as the Problematic ChatGPT Use Scale (Yu et al., 2024) and AI Dependence Scale (Zhang et al., 2025c). As noted earlier, human–AI interaction is still an emerging topic, and the development of AI-related questionnaires and scales has only surged in recent years. Many promising tools have not yet received sufficient attention, and the thematic focuses of these new instruments remain unclear. Therefore, this descriptive study aimed to review existing scale development and validation efforts, uncover the characteristics of currently available tools and the most prominent research constructs, and provide methodological references to guide scholars in selecting research directions and instruments in this field.

Importantly, the present review is positioned as a bibliometric mapping and descriptive narrative synthesis rather than a full systematic review of psychometric quality. Mapping-oriented reviews are useful when a research area is broad, heterogeneous, and rapidly expanding, because they can clarify the size, structure, and conceptual contours of a field before narrower evidence syntheses are feasible (Grant & Booth, 2009; Munn et al., 2018). In this sense, the study makes three contributions. Theoretically, it identifies the constructs that currently organize human-AI interaction measurement. Methodologically, it maps publication trends, collaboration networks, keyword structures, and thematic evolution in this emerging area. Practically, it summarizes frequently used instruments and their validation evidence to support preliminary tool selection. Thus, the aim is not to rank all instruments through a comprehensive psychometric appraisal, but to provide a field-level overview and a starting point for subsequent systematic reviews and empirical scale-selection decisions.

2. Methods

2.1. Data Sources

Web of Science (WoS) and Scopus are the two largest and most widely used academic databases, serving as the foundation for numerous bibliometric analyses (Pranckutė, 2021). Following the methodologies outlined in previous bibliometric studies (Akintunde et al., 2021; Alviz-Meza et al., 2023; Kawuki et al., 2020; Khosravi et al., 2024; Manriquez et al., 2015), and considering the compatibility of our software with the databases, we conducted our bibliometric analysis using the WoS Core Collection and the full Scopus database.

2.2. Search Strategies

We performed a systematic search to retrieve relevant publications. The design of keywords was informed by existing systematic reviews on artificial intelligence (Miller et al., 2025; Temperley et al., 2024; Yin et al., 2021; Zawacki-Richter et al., 2019) and on scale development (Ghasemi et al., 2015; Schellingerhout et al., 2012). The specific search terms are presented in Supplementary A Table S1. Since our focus was on studies devoted to the development and/or validation of scales, we searched within publication titles. The search covered all publications available from the inception of each database up to June 29, 2025. Language was restricted to English.

To make the strategy more transparent, the search terms were organized into two concept blocks: AI-related terms (e.g., artificial intelligence, AI, chatbot, generative AI, large language model) and measurement-instrument terms (e.g., scale, questionnaire, instrument, measure, validation). The title-field restriction was adopted to increase specificity and to reduce retrieval of studies that merely used an

AI-related scale as an auxiliary variable rather than treating the instrument itself as the research object. Records exported from WoS and Scopus were merged, deduplicated, and screened according to the criteria described below.

2.3. Inclusion and Exclusion Criteria

Inclusion criteria were: (1) studies on the development or validation of measurement scales; and (2) scales addressing AI-related behaviors and psychological constructs. Exclusion criteria were: (1) publications without data analysis (non-research papers); and (2) studies using AI for measurement purposes but with outcomes unrelated to AI (e.g., questionnaires designed with AI but measuring unrelated constructs).

During screening, studies were first assessed by title and abstract. Full texts were consulted when eligibility could not be determined from bibliographic information or abstracts. Studies were retained when the scale or questionnaire itself was the main object of development, validation, translation, or psychometric testing. Studies were excluded when AI was used only as an analytical method or when a measurement instrument was used only as an outcome or covariate without instrument-focused analysis.

2.4. Analysis

2.4.1 Bibliometric Analysis

Bibliometric analysis serves as a primary tool for exploring and analyzing unstructured scientific data in publications (Donthu et al., 2021). This method enables researchers to trace the nuanced evolution of specific domains and to identify emerging themes or directions (Donthu et al., 2021). For data analysis, we used the bibliometrix package (v. 4.1.4) in R (v. 4.3.1) (Aria & Cuccurullo, 2017; Derviş, 2019), which facilitates graphical representation of statistical trends and enhances the interpretability of research patterns.

2.4.2 Narrative Review

Automated thematic identification in bibliometric analysis often suffers from ambiguity and limited interpretability. To overcome this limitation, we conducted a qualitative narrative review to systematically categorize research themes. Although this approach does not provide quantitative insights, it is particularly effective in synthesizing the latest knowledge on specific topics and offering a more nuanced understanding of the field (Rother, 2007). In this study, narrative review was primarily used to classify and discuss the measurement tools employed in the included research. Specifically, we adopted an approach similar to thematic analysis, classifying and labeling the tools according to their type and the constructs/outcomes they measured. This work was carried out jointly by two authors, who reached agreement in a committee-style process.

To make this process more transparent, two authors extracted the scale/questionnaire name, target population, AI context, measured construct, and reported validation evidence from abstracts and full texts where available. Initial codes were generated from the construct labels used by original authors and from item/content descriptions. Similar codes were then grouped into broader categories through an inductive process informed by thematic analysis principles (Braun & Clarke, 2006). When one instrument covered several constructs, we coded it according to its primary measurement purpose and recorded secondary features where relevant. Disagreements were resolved through committee-style discussion until consensus was reached. This procedure was designed to support field mapping and tool recommendation rather than a full psychometric quality appraisal.

3. Results

3.1. Study Selection

From the WoS and Scopus databases, we initially retrieved 507 and 943 records, respectively. After removing 464 duplicates, 871 irrelevant studies were excluded based on title and abstract screening. Ultimately, 115 papers were included in the final analysis (Figure 1).

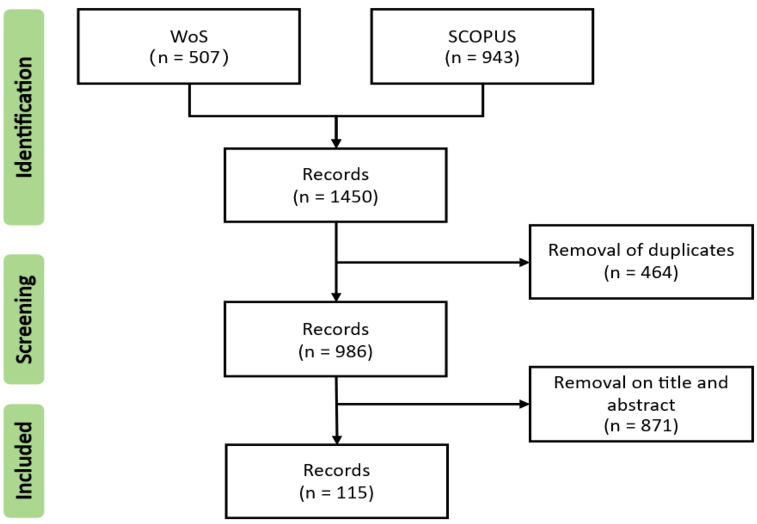


Figure 1. The study selection flow diagram of included research

3.2. Publication Trends and Distribution

The included studies were published between 2007 and 2025 (Figure 2a). The number of publications began to rise sharply in 2022. Regionally, China, Saudi Arabia, the United States, South Korea, and the United Kingdom contributed the highest number of publications, with international collaboration most frequent between the U.S. and China (Figure 2b). Journals that published the most studies included the International Journal of Human–Computer Interaction and Education and Information Technologies (Figure 2c), reflecting a research focus on human–computer interaction and education. Prominent authors included Simone Borsci (Associate Professor, Human Factors & Cognitive Ergonomics, University of Twente), Jinghan Li (National Yunlin University of Science and Technology), and Yuyin Yang (National Yunlin University of Science and Technology). However, their overall number of publications remained relatively low (fewer than five).

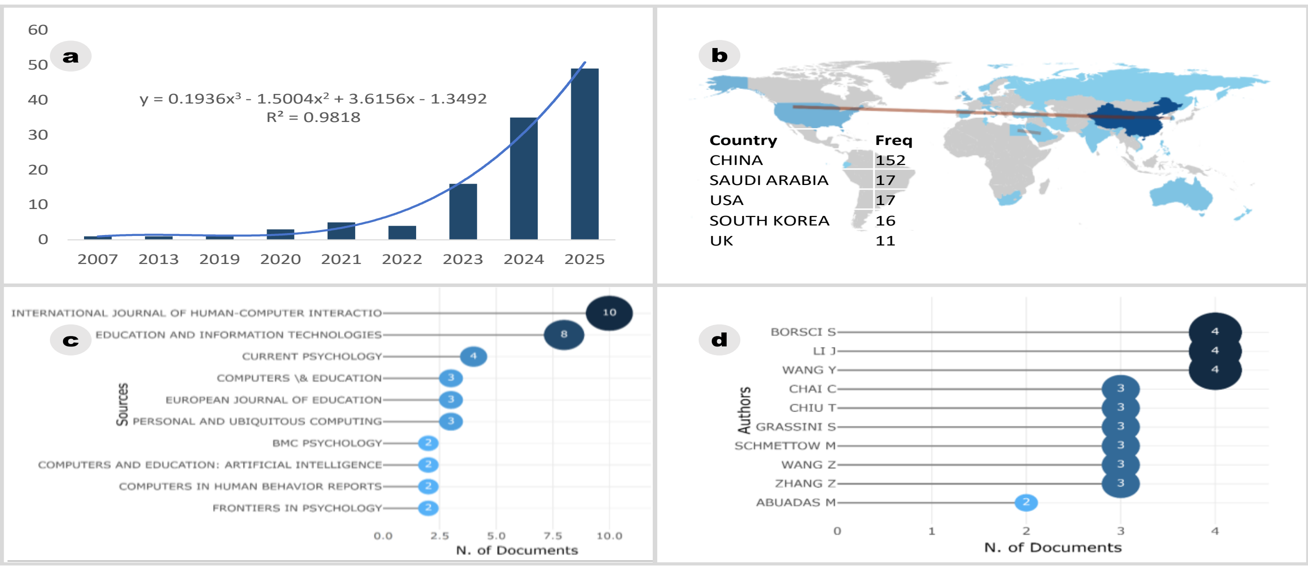
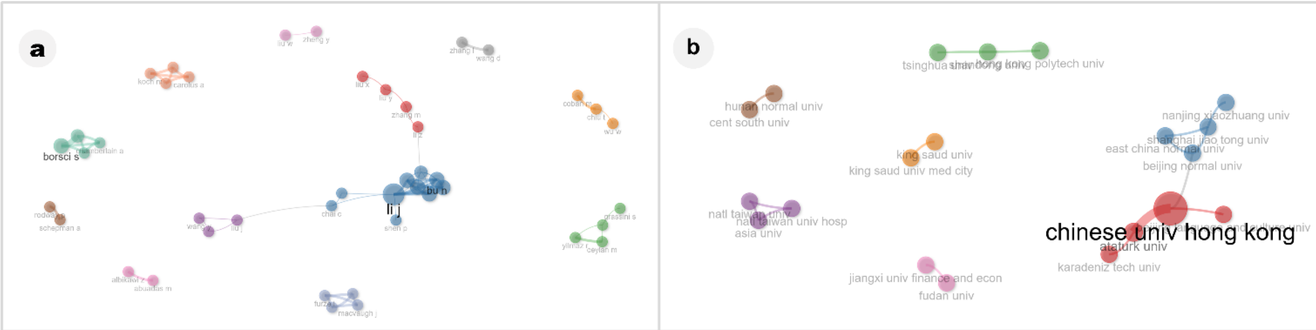


Figure 2. Publication trends by (a) year, (b) region, (c) leading journals, and (d) leading authors Note: In Figure 2b, brown lines represent international collaborations; thicker lines indicate stronger collaboration.

3.3. Author and Institutional Collaboration

As shown in Figure 3, collaboration among authors and institutions was limited, characterized by small clusters and weak connections between them. The network centered on Jinghan Li dominated the author collaboration network. Among institutions, the Chinese University of Hong Kong served as a central hub in the collaboration network and made the largest contribution in terms of publication volume.

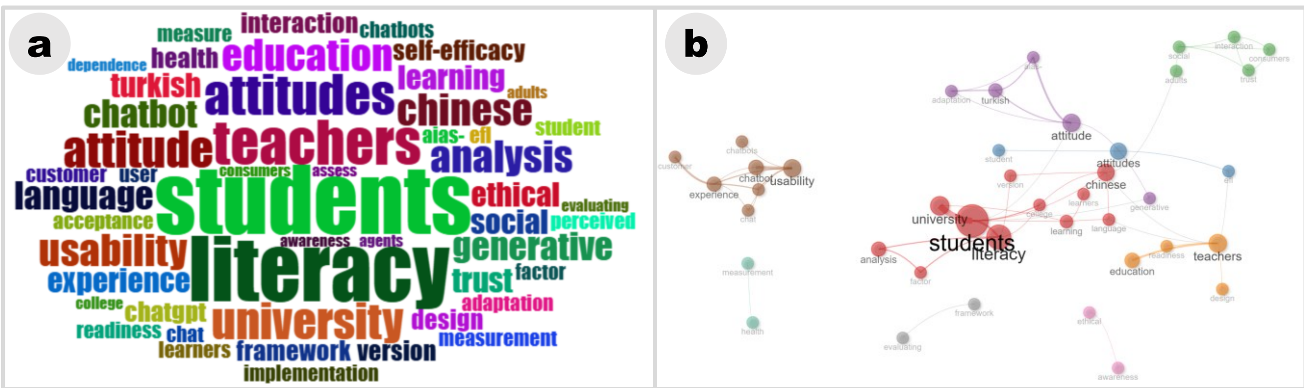


Note: Node size indicates the number of publications; line thickness indicates the strength of co-occurrence across studies.

Figure 3. Collaboration networks among (a) authors and (b) institutions

3.4. Research Keywords and Co-Occurrence Network

To reduce noise, we removed search-related terms (e.g., “artificial intelligence,” “scale”) and other irrelevant keywords (see Supplementary A Table S2). The resulting keyword cloud (Figure 4a) highlighted students and teachers as the most frequent population-related terms, while attitude and literacy were the most frequent construct-related terms. Further analysis identified ten major constructs: attitude (n = 20), literacy (n = 17), usability (n = 8), experience (n = 7), ethics (n = 6), self-efficacy (n = 5), acceptance (n = 4), dependence (n = 3), perception (n = 3), and competence (n = 4). These results underscore the key research focuses. The co-occurrence network (Figure 4b) linked populations, AI types, and constructs, for example: students–universities–literacy, and teachers–education–readiness, reflecting the target populations and contexts of different scales.



Note: In Figure 4b, node colors represent clusters, node size indicates keyword frequency, and distance reflects co-occurrence strength.

Figure 4. (a) Keyword cloud from study titles and (b) co-occurrence network

3.5. Research Themes and Evolution

After excluding irrelevant high-frequency terms (Supplementary A Table S3), we generated a thematic map from title keywords (Figure 5a). To highlight thematic shifts, we also generated thematic maps for studies published before and after 2022 (Figures 5b and 5c), given the publication surge starting that year.

Each theme is characterized by two parameters: density and centrality. Density (Callon density) reflects the internal strength of connections among keywords within a theme, while centrality (Callon centrality) reflects the degree of interaction between a theme and others (Callon et al., 1991; Cobo et al., 2011). Accordingly, the four quadrants of the thematic map are: (1) upper right: motor themes—well-developed and central; (2) lower right: basic themes—fundamental but underdeveloped; (3) upper left: niche themes—well-developed but peripheral; (4) lower left: emerging or declining themes—newly developing or fading topics (Rani et al., 2023).

In the overall thematic map (Figure 5a), attitudes and literacy exhibited high centrality, underscoring their importance. In contrast, anxiety and threat showed low centrality, suggesting peripheral status. Among emerging or declining themes, service appeared, reflecting scale applicability.

The time-based maps revealed that before 2022, no mature and central themes had formed; attitude was central but underdeveloped (Figure 5b). From 2022–2025, attitude became a motor theme, reflecting its maturity and dominance (Figure 5c). Meanwhile, new themes such as fear emerged.

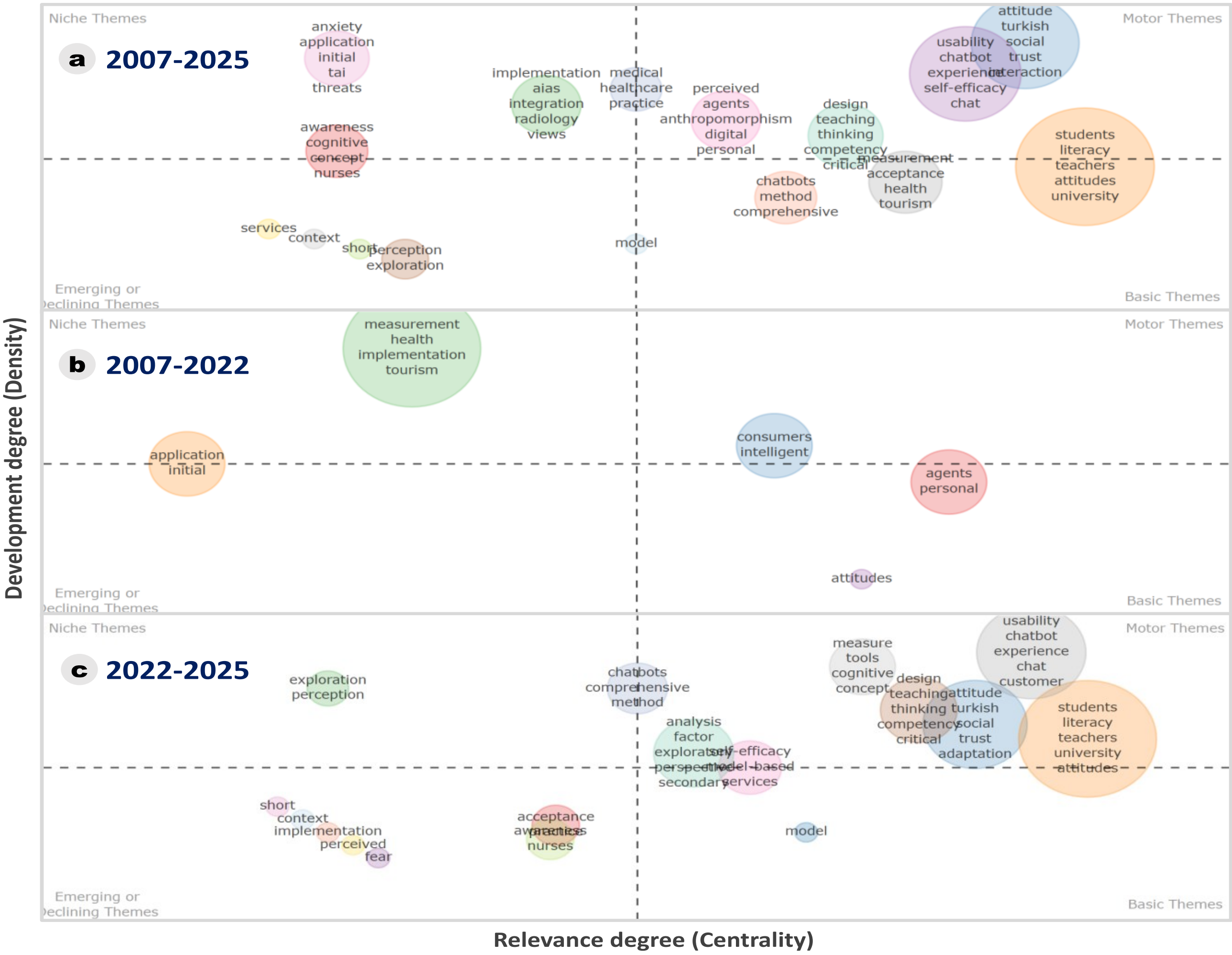


Figure 5. Thematic map and temporal differences

3.6. Questionnaire Classification

Through narrative review of abstracts and full texts, we classified the included scales/questionnaires into preliminary categories (Figure 6). The corresponding studies are listed in Supplementary B Table S1.

AI Readiness Scale for Teachers	2024
Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS)	2021
Teachers' AI Readiness Scale for Chinese as a Foreign Language Education	2025
University Learners' Readiness Scale for ChatGPT-Assisted English Learning	2025

AI Readiness

AI-Enhanced Gamification in Education Scale	2025
Artificial Intelligence Convergence Teaching Expertise Scale for Pre-Service Teachers in Korea	2025
AI-Critical Pedagogy Scale (AICPS)	2025
Language Teachers' Design Thinking Competency in AI-Based Language Teaching Scale (LTDTAILT)	2025
Moral Ascendancy and Dependency in AI Integration (MAD-AI) Scale for Teachers	2025
Artificial Intelligence Learning Intention Scale	2024
Perceived Interactivity of Learner–AI Interaction Scale	2025
Teachers' Competency Scale for Generative AI-Enabled Higher Education	2025
Questionnaire on Artificial Intelligence Training for Teachers	2025
AI Assessment Scale (AIAS)	2024
Artificial Intelligence Assessment Scale (AIAS)	2024

AI Education and Teaching

Artificial Intelligence Self-Efficacy Scale	2024
AI-Supported Teaching Applications Self-Efficacy Scale	2024
Self-Efficacy and Needs Questionnaire for Large Language Model-Based AI Services	2025
Teacher AI Competence Self-Efficacy Scale (TAICS)	2025
Student AI Competency Self-Efficacy Scale (SAICS)	2025

AI users self-efficacy

Perceived Artificial Intelligence Literacy Questionnaire (PAILQ)	2024
Artificial Intelligence Literacy Questionnaire	2023
Affective–Behavioral–Cognitive–Ethical AI Literacy Questionnaire	2024
Multidimensional AI Literacy Questionnaire	2024
Digital Literacy in the Artificial Intelligence Era Scale for College Students	2023
ChatGPT Literacy Scale	2024
Artificial Intelligence Literacy Scale for Teachers (AILST)	2025
Scale for the assessment of non-experts	2023
AI Literacy Scale for Secondary School Students	2025
Artificial Intelligence Literacy Scale	2023
Meta AI Literacy Scale	2024
Arabic Version of the Artificial Intelligence Literacy Scale (AILS)	2024
AI Literacy Scale	2024
Student AI Literacy in L2 Writing Scale	2025
Artificial Intelligence Literacy Scale for Chinese College Students (AILS-CCS)	2024

AI literacy

Fear of Artificial Intelligence Scale	2025
Artificial Intelligence Anxiety Scale for Chinese EFL Teachers	2025
Artificial Intelligence Anxiety Scale	2022
Threats of Artificial Intelligence Scale (TAI)	2021
Threats of Artificial Intelligence Scale (TAI) – Chinese Version	2023
Fear of Missing Out on AI Scale	2025

AI anxiety and fear

Chatbot Usability Scale	2023
Automated Social Presence Scale	2024
ChatGPT-3.5 System Usability Scale	2024
Italian Adaptation of the Chatbot Usability Scale	2023
Bing Chat Usability and User Experience Assessment Scale	2023
Chatbot Usability Scale (BUS-11)	2024
Chatbot Usability Scale (Confirmed Version)	2023
Bot Usability Scale	2025
Perceptions of Bing Chat Search and AI Chatbot Usability Scale	2023

Availability and User Experience

AI Ethical Awareness and Academic Integrity Scale (Higher Education)	2025
AI Social Responsibility in the Consumer Market Scale	2025
AI Ethical Reflection Scale (AIERS) for University Students	2025
Nurses' Ethical Awareness in AI Use Scale	2025

Ethics and social responsibility

Turkish Adaptation of the AI Attitude Scale (AIAS-4)	2025
Turkish Version of the Artificial Intelligence Attitude Scale (AIAS-4)	2025
Turkish Version of the Artificial Intelligence Scale	2025
AI Awareness Scale	2025
AI in Education and EFL Teachers' Attitudes Scale	2025
Generative AI Attitude Scale for EFL Learners (GenAIAS)	2024
Attitudes Toward AI at Work Scale	2024
Artificial Intelligence Technology Risk Perception Scale (AITUTRPS)	2021
EVAIA-1: Attitudinal Assessment Scale Toward Artificial Intelligence	2023
AI Attitude Scale for Nurses	2025
Student Attitudes Toward Artificial Intelligence Scale	2022
Generative AI Attitude Scale for Students	2025
Artificial Intelligence Attitude Scale (AIAS-4)	2023
Semantic Differential Scales for AI Agents	2023
Teachers' Perception of AI Use in Education Scale	2025
AI Acceptance Scale for Interprofessional Education (AAIPE)	2025
Endoscopists' AI Acceptance in Gastrointestinal Endoscopy Scale	2022
Healthcare Professionals' Perceptions of AI Questionnaire	2021
Generative Artificial Intelligence Acceptance Scale	2024
General Attitudes Toward Artificial Intelligence Scale	2020
Perception of AI Creativity Scale	2025
Turkish Version of the AI Attitude Scale (AIAS-4)	2025
AI-Based Interview Attitudes Scale (for University Admissions)	2024
General Attitudes Toward Artificial Intelligence Scale (GAAIS)	2023
Technology Acceptance Model-Based ChatGPT Scale (TAME-ChatGPT)	2025
Attitudes Toward AI in Defense (AAID) Scale	2023
AI-Assisted L2 Learning Attitudes Scale for Chinese College Students	2024
Chinese Version of the General Attitudes Toward Artificial Intelligence Scale	2025

AI attitude and acceptance

Dependence on Artificial Intelligence in University Students Scale	2024
Problematic ChatGPT Use Scale	2024
Large Language Model Dependence Scale	2025
Reliance on Generative AI During Problem-Solving Scale	2025
AI Chatbot Dependence Scale	2025

AI dependency and problematic use

ChatGPT Usage Scale for Foreign Language Learners	2025
Chatbot Use in Air Travel Questionnaire	2020
AI Chat Information Retrieval and Processing Behavior Scale	2025
University FAQ Chatbot Evaluation Questionnaire	2023
Conversational Agents Scale (CAS)	2013
LLM-Powered Counseling Chatbot Evaluation Scale (CES-LCC)	2025
Chatbot–User Interaction Scale	2024
ChatGPT Usage Scale	2024

ChatGPT and Dialogue Proxy Evaluation

Artificial Intelligence Skills Scale	2025
AI Needs in Health Tourism Scale	2022
AI Psychological Anthropomorphism Scale	2024
Personal Digital Assistant Evaluation Scale	2007
Radiologists' Views on AI in Radiology Questionnaire (ATRAI-14)	2024
AI Virtual Streamer Scale (for E-Commerce)	2024
Patients' Views on AI in Radiology Questionnaire	2020
Perceived Intelligence and Anthropomorphism Scale for Intelligent Agents	2019
FAITA–Mental Health: AI Tool Assessment Framework	2024
AI–Digital Life Balance Scale	2025

Others

Critical Thinking Proficiency Scale (for Gen Z ChatGPT Users)	2024
Cognitive Outsourcing Behavior Toward AI Scale	2024
Metacognitive Skills Questionnaire (MCSQ)	2024

Cognitive and Thinking Skills

Customer Experience in AI-Enabled Products Scale	2024
AI Customer Experience Scale	2025
Customer Experience in AI Contexts Scale	2025

Consumer and Customer Experience

Trust Toward AI Social Robots Scale	2021
Trust Scales in Artificial Intelligence Vignettes	2025
Trust in Automation Scale	2025
Social Service Robot Interaction Trust (SSRIT) Scale	2024

AI Trust

Figure 6. Categories of scales/questionnaires identified in included studies

We identified 13 major categories, with additional niche instruments grouped under "others" due to lack of commonality. Figure 6 shows that AI attitude and acceptance constituted the largest category, followed by AI literacy. In contrast, AI cognitive and thinking skills were least represented. Temporally, ethics and social responsibility, self-efficacy, consumer and customer experience, cognitive and thinking skills, and dependency and problematic use emerged after 2024. Notably, some scales covered multiple features (e.g., chatbots problematic use), while others focused narrowly. Therefore, classification was based on primary features, and we emphasize this is a preliminary categorization.

3.7. Most Popular Scales/Questionnaires

Based on the ten most-cited studies, we summarized the nine most frequently used scales/questionnaires. Two of these tested the reliability and validity of the General Attitudes towards Artificial Intelligence Scale (Schepman & Rodway, 2023; Schepman & Rodway, 2020). As shown in Table 1, this scale was the most widely used, with the original study cited 278 times. The second most popular tool was the Artificial Intelligence Literacy Scale (Wang et al., 2023), cited 175 times since 2023. A more recent but rapidly cited tool was the Generative Artificial Intelligence Acceptance Scale (Yilmaz et al., 2024), which received 52 citations within a year of publication. Table 1 also provides details on the validation methods used for these scales, including internal consistency, construct validity, and test–retest reliability.

Table 1. Most popular scales/questionnaires and validation details

Title	Citation	Validation
General Attitudes towards Artificial Intelligence Scale (Schepman & Rodway, 2020)	278	Internal consistency, convergent validity, discriminant validity
Artificial intelligence literacy scale (Wang et al., 2023)	175	Internal consistency, content validity, construct validity
Artificial intelligence anxiety scale (Wang & Wang, 2022)	155	Internal consistency, criterion-related validity, content validity, discriminant validity, convergent validity, and nomological validity
Social Service Robot Interaction Trust scale (Chi et al., 2021)	154	Internal consistency, convergent validity, face validity, discriminant validity, external validity, concurrent validity, and predictive validity
General Attitudes towards Artificial Intelligence Scale (Schepman & Rodway, 2023)	108	Internal consistency, construct validity, convergent and discriminant validity
Acceptance among patients of the implementation of AI in radiology questionnaire (Ongena et al., 2020)	94	Internal consistency
Medical artificial intelligence readiness scale for medical students (Karaca et al., 2021)	88	Internal consistency, face validity, content validity, construct validity
Perceived intelligence and perceived anthropomorphism of personal intelligent agents Scale (Moussawi & Koufaris, 2019)	68	Internal consistency, construct validity, nomological validity
Scale for the assessment of non-experts' AI literacy (Laupichler et al., 2023)	58	None
Generative artificial intelligence acceptance scale (Yilmaz et al., 2024)	52	Internal consistency, test-retest reliability

4. Discussion

4.1. General Discussion

In the current AI era, artificial intelligence is increasingly shaping most aspects of human life. Consequently, human–computer interaction—particularly human–AI interaction—has become a highly visible research domain. Against this backdrop, our study employed bibliometric analysis and narrative review to conduct a descriptive investigation of AI-related measurement tools, aiming to reveal their development and key focuses. Our findings show that AI-related research surged in 2022, but collaboration across countries, institutions, and individual scholars remains limited. Numerous questionnaires have been developed to measure AI attitudes, acceptance, and literacy. At the same time, constructs such as AI anxiety and fear of missing out have emerged as newer research focuses, with preliminary validation of corresponding instruments. Moreover, many studies concentrate on educational contexts and populations such as students and teachers, underscoring their main applications. Taken together, these findings facilitate future sociological research using validated tools in this domain.

From a practical standpoint, the results suggest that researchers seeking broad measures of AI attitudes or literacy may first consider the General Attitudes towards Artificial Intelligence Scale and the Artificial Intelligence Literacy Scale, whereas studies focused on newer risks may consider instruments on anxiety/fear, dependence/problematic use, trust, or user experience according to the target construct. However, tool selection should be guided not only by citation counts but also by construct fit, population fit, language version, and available validity evidence.

4.2. Development Trends and International Collaboration

Our results indicate that research on AI measurement tools began to surge in 2022. By contrast, earlier bibliometric studies suggest that broader AI research started to expand in 2015 (Ho & Wang, 2020). Bibliometric analyses in different fields also reveal domain-specific differences in the timing of this surge (Guo et al., 2020; Knani et al., 2022; Thayyib et al., 2023; Tran et al., 2019). This suggests interdependencies across domains—for example, AI development underpins AI application research. Our findings therefore highlight a relative lag in human–AI interaction research compared with AI development and application.

By 2018, the U.S. was the most productive country in AI research overall, followed by China (Ho & Wang, 2020). In our study, China ranked first in terms of publications, consistent with recent bibliometric analyses on AI (Ivanova et al., 2024; Thayyib et al., 2023). These analyses span education, business and management, engineering and construction, and healthcare, reflecting China's extensive investment in AI research.

Although a substantial number of papers have been published in this area, our findings reveal that academic collaboration remains limited across individuals, institutions, and countries. International collaboration was largely concentrated between China and the U.S. In contrast, fields such as education and shipping exhibit more extensive international research networks on AI (Ivanova et al., 2024; Xiao et al., 2024). We therefore emphasize the need for deeper international collaboration, which would accelerate progress in this field and mitigate regional disparities in research development.

Another notable finding is the concentration of studies in education. Students and teachers appeared repeatedly in the keyword network, and journals with high publication counts included education-oriented outlets. This pattern likely reflects the early and visible impact of generative AI on learning, assessment, academic integrity, and teacher readiness. For the field, this means that education currently provides the richest empirical base for AI-related measurement, but it also cautions against assuming that instruments validated with students or teachers will automatically generalize to clinical, workplace, consumer, or public-service contexts.

4.3. Core Themes and Tools

Through bibliometric and narrative review approaches, this study identified key instruments and central constructs measured in AI-related research. Our findings highlight AI attitudes as a core and mature theme, exhibiting both high centrality and development in scale research. AI literacy also emerged as a central theme, as reflected in keyword analysis. A closer examination of instruments confirmed that the General Attitudes towards Artificial Intelligence Scale (Schepman & Rodway, 2020) and the Artificial Intelligence Literacy Scale (Wang et al., 2023) were the most cited tools. Together, these findings confirm that attitudes and literacy are the most extensively studied variables in this domain. This may stem from earlier studies on attitudes and literacy regarding other technologies, such as computer attitudes (Gressard & Loyd, 1986; Selwyn, 1997) and computer literacy (Sengpiel & Jochems, 2015). These earlier lines of human–technology interaction research provided foundational materials (e.g., item pools) for current AI-related measurement efforts.

Regarding niche and emerging themes, our thematic maps show that anxiety and threat are more peripheral constructs, with lower centrality. Time-segmented maps revealed fear as a newly emerging theme since 2022. In our subjective classification, anxiety, fear, and threat were grouped under AI anxiety and fear. Notably, we found that “AI fear” has been conceptualized from two different perspectives. Albikawi and Abuadas (2025) developed the Fear of AI Scale to measure students’ fear that AI threatens personal competence and survival. By contrast, Fengyi et al. (2025) developed a Fear of Missing Out on AI Scale focusing on concerns about unequal distribution of AI-related benefits. Although novel in the AI field, these constructs build on earlier research, such as technostress (Abuatiq, 2015) and fear of missing out on social media (Abel et al., 2016; Tandon et al., 2021).

We also observed that AI dependency and problematic use form another niche theme. Most tools in this area were developed from 2024 onward (Hou et al., 2025; Li et al., 2025; Morales-García et al., 2024; Yu et al., 2024; Zhang et al., 2025c), with three directly tied to large language models (Li et al., 2025; Yu et al., 2024; Zhang et al., 2025c). This trend aligns with the ChatGPT-driven wave noted in our introduction. These works can be viewed as extensions of technology addiction research into the AI era. Similar niche and emerging themes include AI-related ethics and social responsibility, self-efficacy, consumer and user experience, and cognition and thinking skills, reflecting the diversification of the human–AI interaction field.

Therefore, our practical recommendation is to use the General Attitudes towards Artificial Intelligence Scale for general evaluative orientation, the Artificial Intelligence Literacy Scale for perceived AI competence/literacy, and the Artificial Intelligence Anxiety Scale when anxiety-related responses are the focal outcome. For newer constructs, such as generative AI acceptance or AI dependence, researchers should treat existing tools as promising but still emerging and should report additional validity evidence in their own samples.

4.4. Future Research Directions

Although we identified more than 100 AI-related measurement tools, the field is still at an early stage and faces several limitations and gaps.

Future studies should move from rapid instrument proliferation to cumulative validation. In particular, researchers should report item-generation procedures, content validity, factor structure, internal consistency, test-retest reliability, criterion validity, and measurement invariance when relevant (Boateng et al., 2018; Mokkink et al., 2010). These analyses would make it possible to compare competing tools within the same construct and to determine whether widely cited instruments are also psychometrically robust across populations and contexts.

First, scale design generally requires a clearly defined language base. Yet some studies did not specify the original language of development or the participants’ language background (e.g., Wang et al. (2023), limiting external validity. Given the lack of equivalence across languages, semantic consistency requires rigorous cross-cultural adaptation (Cheung et al., 2020). Moreover, some studies clearly stated that validation was conducted in non-English populations but presented only English-translated items (e.g., Wang and Wang (2022); Liao et al. (2024), omitting the original language version. Without transparent translation processes, subsequent researchers face additional challenges in adaptation. We also found limited cross-cultural translation and validation overall. For example, the most-cited General Attitudes towards Artificial Intelligence Scale (Schepman & Rodway, 2020) has been extended only to Italian (Cicero et al., 2025). In our dataset, most translations and validations occurred in Chinese and Turkish, while other widely spoken languages (e.g., Spanish, French) remain underexplored.

Accordingly, multilingual research should move beyond simple translation. Future studies should specify the source language, publish original and translated items where permitted, document translation/back-translation or expert review procedures, and test measurement invariance across language groups whenever sample sizes allow.

Second, terminology requires further clarification and consistency. For instance, under our category of AI-related anxiety and fear, some instruments (Albikawi & Abuadas, 2025; Wang & Wang, 2022) contain highly similar items. Although anxiety and fear overlap conceptually, they are considered distinct phenomena (Daniel-Watanabe & Fletcher, 2022; Perusini & Fanselow, 2015; Steimer, 2002). Whether these instruments measure substantively different constructs warrants empirical investigation (e.g., correlational or observational comparisons). Moreover, some instruments lack convincing conceptual foundations, raising concerns about validity. As Loscalzo and Giannini (2025) argued, excessive behaviors should not always be labeled as addictions. While no AI addiction scales were identified, related dependence/problematic use tools have recently emerged. The conceptual clarity and appropriateness of such constructs require careful scrutiny, especially since AI use is rapidly integrating into daily life. In some cases, intensive use may resemble dependence without being inherently negative—similar to physical dependence in medical contexts (Horowitz & Taylor, 2023; O'Brien et al., 2006). Therefore, future research should adopt more rigorous conceptualization and terminology.

Finally, because educational settings currently dominate the literature, future research should test whether education-based instruments retain their factor structures and predictive validity in workplaces, healthcare, public administration, and consumer contexts. Within education, more specific measurement questions also deserve attention, such as AI-assisted learning self-regulation, teacher readiness, assessment anxiety, academic integrity concerns, and student dependence on generative AI tools. Such domain-specific work would help the field move from general attitudes toward more actionable constructs.

4.5. Limitations

Several limitations should be noted. First, due to software compatibility constraints, our study only included publications from WoS and Scopus, potentially omitting relevant studies from other sources, preprints, dissertations, or regional databases. Second, our title-only strategy improved specificity for scale-focused publications but may have missed studies whose titles did not explicitly mention scale development or validation. Third, the English-language restriction leaves non-English research unexplored. Finally, because the purpose of this study was bibliometric mapping and narrative categorization, we did not conduct a full systematic review of each instrument's psychometric quality. Future reviews could broaden databases and languages, search abstracts/keywords, and conduct construct-specific systematic appraisals of measurement properties.

5. Conclusion

This study conducted a bibliometric and descriptive narrative analysis of measurement tools related to human-AI interaction, aiming to reveal major themes, key instruments, and stages of development in this emerging field. Its main contribution is to map the rapidly expanding measurement landscape, identify prominent constructs such as attitudes and literacy, and summarize commonly used instruments that can guide preliminary tool selection. The findings suggest that the field is expanding quickly but remains fragmented, with limited collaboration, uneven language coverage, and insufficient cumulative validation across populations and contexts. We therefore call for increased international collaboration, more transparent cross-cultural adaptation, and domain-specific validation work, especially in education and other high-use settings. These efforts can support more rigorous psychological and sociological research on human-AI interaction.

Ethics approval and consent to participate

Not applicable.

Consent for Participation and Publication

Not applicable.

Availability of data and materials

The data underlying this article will be shared on reasonable request to the corresponding author.

Competing interests

The authors declare they have no competing interests.

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Authors' contributions

Conceptualization: Hansen Li; Formal analysis: Hansen Li, Yike Li, and Qingqing Li; Methodology: Hansen Li, Xing Zhang, and Lunxin Chen; Project administration: Hansen Li; Supervision: Hansen Li; Writing-original draft: Hansen Li and Xing Zhang; Writing-review and editing: Hengzhi Deng, Qingqing Li, Zhengyang Mei, and Yike Li.

Declaration of Artificial Intelligence Use

In this study, artificial intelligence tools (ChatGPT 5.0) were used solely for language editing and translation purposes. These tools did not contribute to the generation, analysis, or interpretation of data, nor to the formulation of scientific conclusions. All research design, data collection, statistical analyses, and interpretations were conducted exclusively by the authors.

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