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# UNDERSTANDING EMPLOYEE ATTITUDES TOWARD ARTIFICIAL INTELLIGENCE IN THE WORKPLACE: A SYSTEMATIC REVIEW OF ATTITUDE DEFINITIONS AND MEASUREMENTS

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**Abstract.** This study aims to provide a comprehensive synthesis of existing empirical research on employee attitudes toward artificial intelligence (AI) in the workplace, with a particular focus on how these attitudes are defined and measured. Therefore, systematic literature review was performed. Following PRISMA guidelines, search conducted in two databases, EBSCOhost and Scopus, yielded 642 records, of which 29 met the inclusion criteria. The included studies, published between 2021–2025, covered a broad geographic and sectoral range, encompassing the United States, Europe, Asia, the Middle East, and involved various occupational groups, most commonly general employees, managers, and HR professionals. Review findings indicate that employee attitudes are conceptualized as a multi-dimensional phenomenon, most commonly situated within a cognitive–affective framework. However, the methods used to measure attitudes vary widely, with studies drawing on a combination of established models, adapted scales, and context-specific instruments, which in turn restricts the comparability of results across studies. Drawing from human-centered perspective, this study is timely in highlighting the need to clearly define fundamental employee attitudes toward AI, to employ a validated method to measure them, thereby enabling comparability in future research, and supporting organizations to implement and use AI effectively.

**Keywords:** artificial intelligence, AI, workplace, employee attitudes, measurements, systematic literature review.

**JEL Classification:** M54, O33.

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## 1. Introduction

The 4th Industrial Revolution, which is currently unfolding, is characterized by the ongoing integration of advanced technologies into the physical and biological domains, particularly through the Internet of Things (Navarro et al., 2023) with artificial intelligence (AI) serving as its core technological enabler (Darko et al., 2020). The increasing adoption of AI technologies within organizations is both evident and accelerating (Bankins et al., 2023), driving a paradigm shift in how organizations operate, offering the potential to increase efficiency and effectiveness in various organizational areas (Suseno et al., 2022). Recent studies are already seeking to improve approaches for implementing AI in organizations (e.g., Almashawreh et al., 2024), examining key factors that shape readiness to adopt AI (e.g., Benhayoun et al., 2025), and uncovering a range of implications for organizations seeking to enhance learning effectiveness by integrating one of the most widely used generative AI tools into their workflows (e.g., Korayim et al., 2025). Considering projections that AI will likely be adopted by organizations of all sizes and from diverse regions in the near future (Łukasik-Stachowiak, 2023), gaining insight into employees' attitudes on AI adoption may be a key early step in effectively implementing and using AI for organizations and for both current and potential employees (Park et al., 2024).

It is already established that employee attitudes toward AI play an important role in this context (e.g., Almashawreh et al., 2024; Cao et al., 2021; Park et al., 2024). Studies indicate that employees with positive attitudes are more likely to adopt AI, whereas heightened anxiety is associated with lower readiness for adoption (Suseno et al., 2022). Positive attitudes have been identified as a critical condition for technology acceptance (Almashawreh et al., 2024), and prior work has underscored the role of risk perceptions in shaping attitudes and intentions toward novel technologies (Ratta et al., 2025). In human resource (HR) field, research findings reveal that positive AI attitudes not only significantly enhance use of HR AI-driven tools, but also can improve both rational and intuitive decision-making, suggesting AI serves as a powerful augmentation tool for managerial capabilities (Arora et al., 2025). In addition, reducing AI-related anxiety and job insecurity, while increasing perceived usefulness, may therefore promote more favorable employee attitudes toward AI and shape subsequent behaviors and work experiences (Park et al., 2024).

Although research in this area is steadily growing, the existing literature remains fragmented and comparatively limited, concerning the psychological components that constitute such attitudes (Park et al., 2024), especially from human-centered perspective rather than organizational or technological approach (Cao et al., 2021). Furthermore, some scholars (e.g., Park et al., 2024) have noted that current measurement approaches tend to emphasize functional aspects, without adequately addressing the broader range of cognitive and affective dimensions, thereby leaving unresolved questions about how attitudes toward AI in the workplace should be measured. Clarifying how attitudes are defined and measured is essential for advancing theoretical development, enabling more consistent empirical investigation, and supporting further research on employee attitudes, as well as organizational practices. Therefore, this systematic literature review aims to (a) identify and synthesize existing empirical studies that examine employee attitudes toward AI in the workplace, (b) analyze how these attitudes are conceptually defined and (c) how they are empirically measured.

The remaining paper is structured as follows: a methodology section that outlines the research questions, data sources, search strategy, eligibility criteria, study selection, and quality assessment; a results section reporting the findings of the systematic review, including the characteristics of the included studies, the ways employee attitudes toward AI are conceptualized, and the methods used to measure these attitudes. The paper concludes with sections on discussion and conclusions that present the theoretical and practical implications of the study, acknowledge the limitations of this review, and suggest directions for future research.

## 2. Methods

In the following section, the research questions of this study are outlined, along with the selected method used to address them, as well as the data sources, search strategy, eligibility criteria, study selection process, and the approach to quality assessment of the studies analyzed.

### 2.1. Research questions

In line with the aim of this review, to provide a comprehensive synthesis of existing empirical research on employee attitudes toward AI in the workplace, with a particular focus on how these attitudes are defined and measured, the following research questions were formulated:

(a) what is the scope and what are the characteristics of existing empirical research on employee attitudes toward AI technologies in organizational contexts;
(b) how are employee attitudes toward AI conceptually defined in the reviewed studies;
(c) how are employee attitudes toward AI empirically measured across different studies?

To address these questions, a systematic literature review was carried out, as such reviews remain the most reliable method for examining and synthesizing evidence from diverse sources (Uttley et al., 2023). The review was conducted in accordance with the PRISMA 2020 guidelines (Page et al., 2021). Additionally, systematic review protocol (provided in the Supplementary Material) was developed to outline the background, eligibility criteria, search strategy, and quality assessment procedures. This protocol served as a guiding framework throughout the implementation of the review.

### 2.2. Data sources and search strategy

Two databases were selected to identify relevant empirical studies: EBSCOhost and Scopus. EBSCOhost offers access to a broad range of peer-reviewed literature in psychology, education, and business, making it especially suitable for research related to employee attitudes and organizational behavior in the context of AI. Scopus, as a comprehensive multidisciplinary database, ensures coverage across management, technology adoption, and interdisciplinary AI research. The absence of additional databases is addressed in the discussion section.

Initial exploratory searches were conducted via Google Scholar to test combinations of keywords and inform the formulation of search strings. Final search strings were developed iteratively using synonym expansion tools (thesaurus.com) and AI-assisted refinement (ChatGPT-4o), ensuring terminological precision and conceptual clarity. Main keywords for algorithm developed: [(attitude* OR perception* OR acceptance OR resistance OR trust OR belief* OR "emotional response*" OR skepticism OR "algorithm aversion") AND ("artificial intelligence" OR AI OR "machine learning" OR automation OR "intelligent technolog*" OR "algorithmic decision*" OR "autonomous technolog*") AND (employee* OR manager* OR worker* OR staff OR personnel OR leader* OR professional* OR occupational) AND ("human resource*" OR HR OR workplace OR organization* OR corporate OR job OR work-related) AND (definition* OR dimension* OR classification* OR measure* OR scale* OR questionnaire* OR instrument* OR survey*], which was modified to meet the specific requirements of each database employed.

The review included only peer-reviewed empirical articles, written in English and published from 2010 onward, and excluded studies involving clients or students. The complete search strategy algorithm is presented in

Supplementary Material (see Table 1). In EBSCOhost, search was conducted across “All Fields,” while in Scopus, the “Advanced query” function and subject filters (Psychology, Social Sciences, Business, Management and Accounting) were applied to refine results. All identified records were imported into Mendeley for reference management, and duplicates were removed using the software’s built-in functions. Further data extraction and tracking were conducted using Microsoft Excel.

## 2.3. Eligibility criteria and study selection

The eligibility criteria were developed based on the focus and scope of the review and are summarized in Table 1. For detailed eligibility criteria, see the Supplementary Material (see Table 2). Studies were included if they met the following conditions: (1) reported empirical research (quantitative or mixed methods), (2) focused on employee attitudes toward artificial intelligence (including perceptions, beliefs, acceptance, resistance, trust, fear, or intention to use), (3) included employees or managers in public or private organizations as the study population, and (4) explicitly referenced artificial intelligence technologies, such as machine learning, decision-making systems, robotics, chatbots, or virtual assistants. Exclusion criteria applied to studies that focused on other populations (e.g., students, customers), paid only marginal attention to employee perspectives, or did not have a clear conceptual focus on AI technologies. Non-empirical publications were only included if they contributed substantial conceptual clarification or typologies of employee attitudes toward AI. The screening was conducted by the primary reviewer (RB), with a second reviewer (AE) consulted in cases of uncertainty to ensure consistency in the application of inclusion and exclusion criteria.

For all included studies, key data was systematically extracted and recorded in a structured spreadsheet using Microsoft Excel. Extracted variables included general study characteristics (e.g., authors, year, country), target population characteristics (e.g., employee roles, organizational context), methodological design (e.g., research type, data collection and analysis methods), AI-related features (specific technologies addressed), and other information directly relevant to the review. Special attention was paid to how employee attitudes toward AI were defined and operationalised, as well as to the measurement instruments and attitude dimensions employed across studies. Following study selection and data extraction, all included records underwent a structured quality assessment, as described in the subsequent section.

It is noted that for efficiency and consistency in article analysis, the Adobe Acrobat AI Assistant was used to verify the accuracy and completeness of relevant content extracted from PDF documents, ensuring that no critical information was overlooked.

## 2.4. Quality assessment

The quality of included studies was evaluated using a structured checklist (12 questions) adapted for this review, focusing on methodological clarity, measurement validity, and scientific rigor. Drawing on this checklist, three overarching quality appraisal categories were established, which served as additional exclusion criteria during the final records evaluation (measurement of attitudes toward artificial intelligence is not clearly defined or lacks evidence of reliability/validity; data analysis is insufficiently described or lacks methodological rigor; lacks scholarly credibility due to questionable publication source or authorship). Full details of the appraisal process, criteria, and scoring are provided in the Supplementary Material. Notably, during the quality assessment stage, ChatGPT-4o’s deep search functionality was employed to verify extracted information and to cross-check the consistency of quality appraisal decisions.

**Table 1.** Eligibility criteria

| | Inclusion criteria | Exclusion criteria |
|---|---|---|
| Study design | Empirical research: quantitative or mixed-method studies, including experimental, quasi-experimental, cross-sectional, longitudinal, and intervention designs | Non-empirical publications unless they explicitly define, conceptualize, or classify employee attitudes toward AI |
| Variable of interest | Employee attitudes toward AI, including perceptions, beliefs, acceptance, resistance, fears, trust, emotional reactions, or intentions to use AI | Studies where employee attitudes are addressed only peripherally or without clear definition or focus |
| Target population | Employees (including subordinates and managers) in public or private organizations; general workforce or clearly defined employee sub-groups | Studies focused exclusively on customers, consumers, students, or external stakeholders |
| AI technology specification | Studies that clearly specify AI technologies (e.g., machine learning systems, AI-driven decision-making tools, robotics, chatbots, virtual assistants, or algorithms explicitly labeled as AI) | Studies on general technology, automation, or digital transformation without explicit mention of AI |
| Publication type | Peer-reviewed journal articles, book chapters, published conference papers, research reports | Any other formats (e.g., theses, dissertations, unpublished materials) |
| Publication date | From 2010 onwards | Published before 2010 |
| Publication language | English | Any other language |

## 3. Results

In this section, the findings that address the research questions of this study are presented. First, the characteristics of existing empirical research on employee attitudes toward AI technologies in organizational settings are described. Second, the ways in which these attitudes are conceptualized are outlined. Finally, the measures used to measure these attitudes across the included studies are analyzed.

### 3.1. Characteristics of included studies

The development of this systematic review commenced in May 2025. The literature search was carried out in June 2025, and data analysis and manuscript preparation took place in July 2025. A three-stage PRISMA 2020 process was applied, comprising identification, screening (with eligibility assessment embedded), and inclusion. The complete screening and selection process is illustrated in the flow chart (see Figure 1).

Following the final screening, 29 empirical studies were included, the majority of which were published in 2023–2025 (see Figure 2). This suggests that the topic is both current and still developing. It is reasonable to expect that the figures will increase over the next few years.

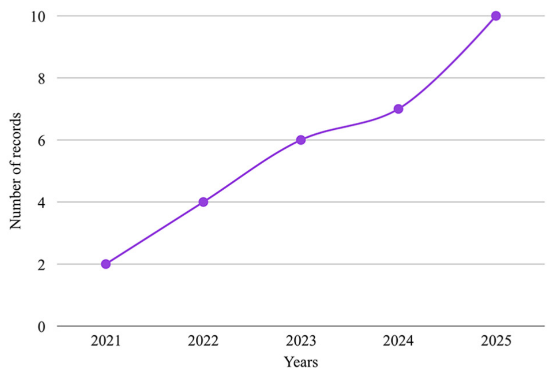


**Figure 2.** Reviewed studies timeline

Reviewed studies were geographically diverse, though most were concentrated in the United States (n = 7). Other studies were carried out in Europe (n = 6), Asia outside the Middle East (n = 6), and the Middle East (n = 4), with smaller representations from Africa (n = 1) and Oceania (n = 1), alongside one study that focused on a global organization. One of these studies included participants from both the United States and the United Kingdom, and was therefore counted under both regions. In addition,

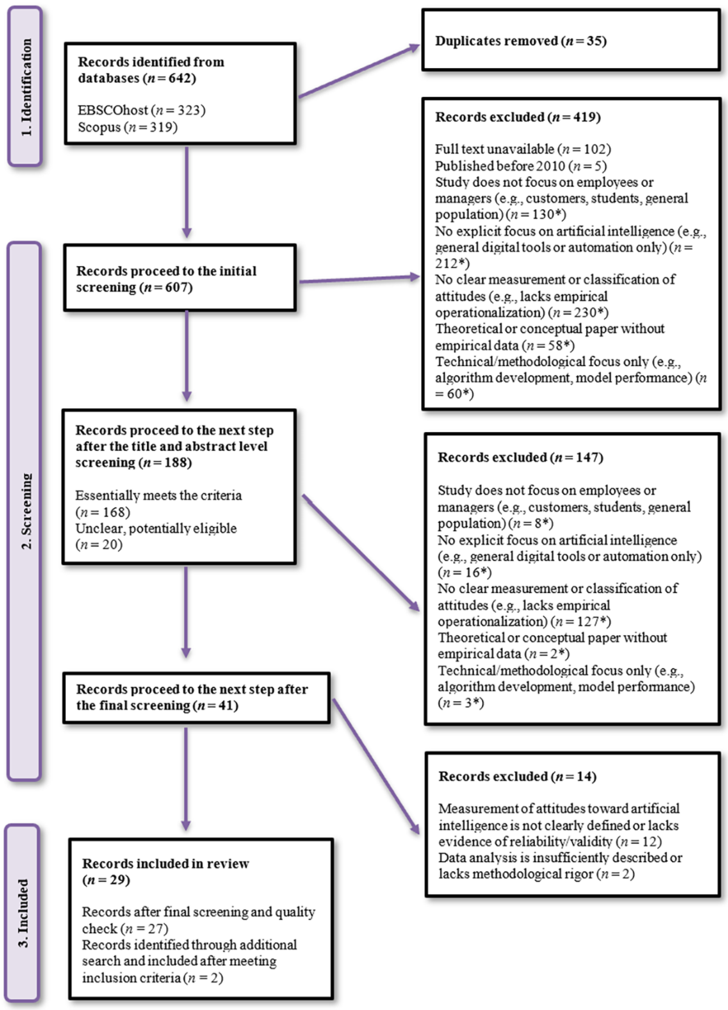


**Figure 1.** Flowchart of the screening process

*Note*: *Some articles were excluded based on more than one criterion; thus, the total number of exclusions exceeds the number of unique articles.

four studies did not explicitly state their geographic location, though the data could be inferred as originating from the United States (1), the United States, Austria, and Kuwait (1), Turkey (1), and India (1).

Across the reviewed studies, the most frequently examined groups were general employees across various functions (n = 10) and managers or executives at different organizational levels (n = 8). HR professionals were the focus in 5 studies, while sector-specific professionals outside of HR (e.g., business, healthcare, design) accounted in 4. One study employed a mixed sample, including AI developers, product owners, and managers, while another study investigated pre-service teachers (see Figure 3). Due to identical percentage values, the two subsequent groups are shown as a single segment in the figure.

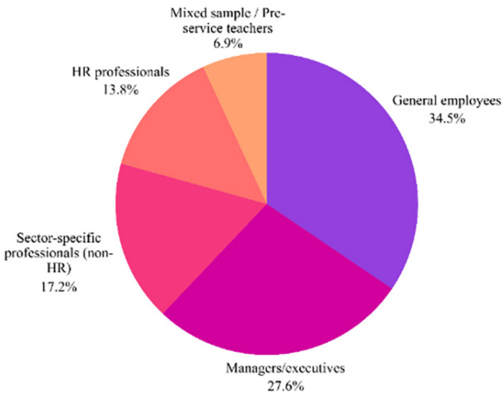


**Figure 3.** Distribution of target groups across reviewed studies

Industry-wise, most studies have been conducted across sectors, covering both public and private organizations, mixed ownership structures, or broad national economies. Healthcare-related settings were examined in 3 studies, while finance and banking appeared in 6. Information technology and digital services were addressed in 3 studies, and professional services such as design, auditing, human resources, consultancy, and psychotherapy were represented in 5. Education-related contexts appeared in 2 studies, and hospitality was investigated in 1. Marketing and customer service employees were studied in 2, and manufacturing, automotive, and construction industries in 3. Finally, 4 studies did not specify a particular industry focus.

### 3.2. Conceptualization of employee attitudes toward AI

The following table provides a comprehensive overview of the key research focuses and constructs analyzed across the reviewed studies. It highlights the frequency with which specific variables were utilized to measure the spread and impact of AI in the workplace (see Table 2).

The key focus of research is on technology acceptance (performance/effort expectancy, perceived usefulness, ease of use), attitudes toward AI as such (positive, negative, instrumental), and trust (emotional, cognitive, organizational, and system-related). Behavioral intention and concerns/threats (job insecurity, perceived risk, anxiety) also feature prominently. Fewer studies address social influence, organizational factors (management support,

**Table 2.** Key focus and constructs of attitudes analyzed across reviewed studies

| Key focus | Main constructs | Studies (n) | Author(s) |
|---|---|---|---|
| Technology acceptance | Performance Expectancy, Effort Expectancy, Perceived Usefulness, Ease of Use, Facilitating Conditions, Self-Efficacy | 12 | Alrishan (2023); Babamiri et al. (2022); Benhayoun et al. (2025); Cao et al. (2021); Chen and Zhou (2022); Eftimov and Kitanovikj (2023); Hmoud and Várallyai (2021); Marimon et al. (2025); Papakonstantinidis et al. (2024); Ratta et al. (2025); Yang (2024); Zhang (2024) |
| Attitudes toward AI | Positive, Negative, Instrumental attitudes, Attitude toward AI adoption | 12 | Almashawreh et al. (2024); Cao et al. (2021); Daly et al. (2025); Emre Taşgit et al. (2023); Ghazy and Fedorova (2022); Hmoud and Várallyai (2021); Korayim et al. (2025); Manresa et al. (2025); Papakonstantinidis et al. (2024); Revillod (2024); Suseno et al. (2022) |
| Trust | General trust, Emotional/ Cognitive/Organizational trust, Trust in AI/chatbot/GenAI, Trust in functionality/reliability/data protection | 11 | Daly et al. (2025); Do et al. (2025); Gkinko and Elbanna (2023); Hmoud and Várallyai (2021); Manresa et al. (2025); Marimon et al. (2025); Papakonstantinidis et al. (2024); Ratta et al. (2025); Swinger et al. (2025); Wang et al. (2023); Wang et al. (2024) |
| Behavioral intention | Intention to Use, Behavioral Intention, Adoption Intention, Intention to Recommend | 9 | Alrishan (2023); Benhayoun et al. (2025); Cao et al. (2021); Eftimov and Kitanovikj (2023); Papakonstantinidis et al. (2024); Ratta et al. (2025); Wang et al. (2024); Yang (2024); Zhang (2024) |
| Concerns / Threats | Perceived Threat, AI/Job Replacement Anxiety, Job Insecurity, Perceived Risk, Uncertainty | 8 | Cao et al. (2021); Park et al. (2024); Presbitero and Teng-Calleja (2023); Ratta et al. (2025); Revillod (2024); Suseno et al. (2022); Tandon et al. (2025); Yang (2024) |
| Performance outcomes | Task Performance, Employee Performance, Adaptive Performance, Work Engagement | 5 | Do et al. (2025); Eftimov and Kitanovikj (2023); Emre Taşgit et al. (2023); Manresa et al. (2025); Marimon et al. (2025) |

*End of Table 2*

| Key focus | Main constructs | Studies (n) | Author(s) |
|---|---|---|---|
| Social factors | Social Influence, Peer Influence | 4 | Cao et al. (2021); Eftimov and Kitanovikj (2023); Ratta et al. (2025); Zhang (2024) |
| Organizational factors | Management Support, Training, Reward System, Top Management Commitment | 4 | Almashawreh et al. (2024); Benhayoun et al. (2025); Chen and Zhou (2022); Swinger et al. (2025) |
| AI perceptions | Humanlikeness, Adaptability, Quality, Beliefs about AI, AI Capabilities | 4 | Babamiri et al. (2022); Park et al. (2024); Suseno et al. (2022); Swinger et al. (2025) |
| Motivation | Intrinsic Motivation, Extrinsic Motivation | 3 | Babamiri et al. (2022); Papakonstantinidis et al. (2024); Yang (2024) |
| Ethics / Privacy / Security | Privacy Protection, Perceived Security, Ethics in Beneficence, Transparency | 3 | Revillod (2024); Swinger et al. (2025); Wang et al. (2024) |
| Personal concerns | Personal Development Concerns, Well-being Concerns | 2 | Cao et al. (2021); Revillod (2024) |

training), motivation, ethics/privacy, and AI perceptions (humanlikeness, adaptability). Performance outcomes (employee performance, work engagement) represent an emerging focus. Overall, the literature clusters around acceptance, trust, attitudes, and intentions, with growing attention to risks, ethics, and organizational context.

It should be emphasized, that employee attitudes toward AI are conceptualized variably across studies, reflecting diverse theoretical frameworks. Notably, only few studies provide a clear or exclusive definition of the attitude construct.

In Cao et al. (2021, p. 5) study, based on Dwivedi et al. (2017) attitude is seen as "an individual's positive or negative feelings about using AI for organizational decision-making". Revillod (2024), based on prior research, also differs attitudes into two groups of positive and negative, where positive refers to perceptions of AI innovativeness and optimism towards AI, while negative represents individuals' discomfort or insecurity toward AI. Ghazy and Fedorova (2022), in their work on employee attitudes and acceptance of service robots, define attitudes as evaluative judgments, shaped through complex psychological processes, that reflect positive or negative emotions, that function as antecedents of intentions and subsequent behaviors. Emre Taşgit et al. (2023) determine attitudes as positive and negative ones as well, although, do not provide definitions. In general, four studies applied a definition of attitudes as positive or negative feelings toward AI.

The other two studies conceptualize attitudes toward AI as a tripartite construct. Daly et al. (2025) state that, based on concepts in the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), attitudes towards AI are considered to be positive or negative, but also explores additional – instrumental – dimension. Positive attitude describes openness to using and perceiving AI as useful, negative – relates to a lack of autonomy in relation to AI, and instrumental attitude depends on rational justification for continued use (Daly et al., 2025). Suseno et al. (2022) attitude explains under 3 domains: cognitive, affective and behavioural, as based on tripartite model of attitude (TMA), where cognitive reflects perceptual responses to AI, affective – capturing emotions and moods toward AI, and behavioural element is based on past experience or future intentions toward AI.

The study by Park et al. (2024) provides the most comprehensive description and explanation of attitude construct, where based on prior research, attitude toward AI is seen as a multifaceted construct encompassing dimensions from functionality to socio-emotionality, and ranging from appreciative to aversive responses. Specifically, drawing on Eagly and Chaiken (1993, 2007) works (as cited in Park et al., 2024, p. 921), attitude is defined as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor", when both, cognitive and affective constructs, are undertaking. Authors deliberately exclude behavioural intention from the conceptualization of attitude, emphasizing that, this intention is more accurately understood as an outcome of attitudes, guiding specific actions (Park et al., 2024). Also, authors state that in order to successfully adopt and integrate AI in organizations, it is crucial to understand and manage employee attitudes toward it (Park et al., 2024).

Although explicit definitions of employee attitudes toward AI were not provided in other studies, they analyzed constructs, that can be interpreted as attitudinal in nature. Most, drawn on UTAUT, explored performance expectancy, effort expectancy, performance expectancy, perceived usefulness, etc. (a detailed summary is provided in Table 2). It is also evident that several of the reviewed studies addressed the concept of trust, however, its definition varied and was not consistently provided in all cases. In total, six studies offered an explicit definition or at least some information about trust in their findings.

Drawing on Bakker et al. (2023), Marimon et al. (2025, p. 7077) define trust as one that "can represent the motivational resource leading to employee engagement and consequently to increased performance through the so-called "gain cycle"". Gkinko and Elbanna (2023), who investigated trust toward the AI chatbot, reveal 3 layers – emotional, cognitive and institutional trust, and states that within organizations, teams, and technology-related domains, trust emerges as a critical construct. Hmoud and Várallyai (2021), studied HR leaders' trust in AI application in talent acquisition, explain important predictors (seen as beliefs) of trust: technical competence, reliability, and credibility. Wang et al. (2023) study on trust in chatbots show that trust is a multidimensional construct, developed through employees' perceptions of functionality, reliability, and also data protection. Swinger et al. (2025) see trust from two perspectives: for the trustor, it is understood as the willingness to take risks, whereas for the trustee, it is conceptualized as trustworthiness, reflected in their ability, benevolence, and integrity. Do et al. (2025) state that high trust in AI indicates employees' confidence in the systems' reliability, competence, and benevolence.

## 3.3. Methods of measuring employee attitudes toward AI

Of the 29 studies reviewed, most used a quantitative design (through online surveys, multi-item Likert-scale self-report questionnaires), while 4 adopted a qualitative design, specifically thematic analysis (n = 2), inductive analysis (n = 1), and a grounded theory approach (n = 1). In all included studies, clear information was provided regarding the scales / questions / methods used to measure employee attitudes toward AI, along with the sources or authors on whose work these methods were based. The reported reliability and validity results for all scales and questionnaires were deemed acceptable, with the exception of one study for which no such information could be identified. Measurement approaches summarized in the Table 3.

Different methods are used to measure employee attitudes toward AI in the workplace, with no single scale

**Table 3.** Measurement approaches of employee attitudes toward AI

| Author(s) | Data collection method / tool |
|---|---|
| Cao et al. (2021) | 49-item Integrated AI acceptance-avoidance model (IAAAM), measured by a 7-point Likert scale |
| Hmoud and Várallyai (2021) | 26-item scale developed based on different sources (Teo et al., 2007; Martins et al., 2016), (Thatcher et al., 2011; Choi & Ji, 2015), (Venkatesh et al., 2003; Voermans & Van Veldhoven, 2007), measured by a 5-point Likert scale |
| Babamiri et al. (2022) | 36-item Service Robot Integration Willingness Scale (Lu et al., 2019); 14-item Human-robot trust scale (Schaefer, 2013); 4-item STARA scale |
| Chen and Zhou (2022) | 5 items on perceived ease of use (Segars & Grover 1993); 3 items on Self-efficacy (Compeau & Higgins 1995); 6 items on Perceived management support (Leonard-Barton & Deschamps, 1988); 5 items on Acceptance of AI (Venkatesh & Davis, 2000) |
| Ghazy and Fedorova (2022) | 10 items on psychological attitude and 12 items on social attitude, based on different sources (Bröhl et al., 2016; Nomura et al., 2004; Weiss et al., 2008), measured by a 5-point Likert scale |
| Suseno et al. (2022) | 5-item Change readiness for AI adoption scale developed by Rafferty and Minbashian (2019); 10-item scale on Beliefs about AI developed by Durndell and Haag (2002); 19-item scale on AI anxiety developed by Durndell and Haag (2002); all items measured using a 7-point Likert scale |
| Alrishan (2023) | Teachers' intention to adopt ChatGPT assessed with 4 items adapted from Lee et al. (2003) and Venkatesh and Bala (2008); 6 items on perceived usefulness and 5 items on ease of use adapted from Davis (1989); 4 items on teachers' support were utilized from Metheny et al. (2008); 6 items on learning value adapted by Sitar-Taut & Mican (2021) |
| Eftimov and Kitanovikj (2023) | 16-item scale based on UTAUT model, measured by a 5-point Likert scale |
| Emre Taşgit et al. (2023) | 16-item scale based on the Artificial Intelligence Acceptance-Avoidance Scale (Cao et al., 2021) and the Artificial Intelligence Anxiety Scale (Wang & Wang, 2019), measured by a 5-point Likert scale |
| Gkinko and Elbanna (2023) | Based on recommendations of Gioia, Corley, and Hamilton (2013) for inductive analysis, which consisted of three stages (descriptive codes, codes grouped into themes, resulting themes aggregated into three dimensions) |
| Presbitero and Teng-Calleja (2023) | 4-item scale on perceptions on AI adapted from Brougham & Haar (2018), measured by a 5-point Likert scale |
| Wang et al. (2023) | 3 items on trust in functionality and 4 items on trust in reliability adapted from Tams et al. (2018); 3 items on trust in data protection adapted from Al-Natour et al. (2020); all items measured using a 7-point Likert scale |
| Almashawreh et al. (2024) | Constructs on Managerial support, Training, Reward system, Attitude, and Usage, 5-item each, adapted from various sources (see detailed information in Table 2), measured by a 5-point Likert scale |
| Papakonstantinidis et al. (2024) | 22-item questionnaire based on NCGAS scale (adapted from Liu et al., 2013) and TAM questionnaire (Davies, 1989) |
| Park et al. (2024) | 25-item Attitudes towards AI Application at Work (AAAW) scale, measured by a 5-point Likert scale |
| Revillod (2024) | 24-item Integrated AI acceptance–avoidance model (IAAAM) by Cao et al. (2021), and 20-item General Attitudes towards Artificial Intelligence Scale (GAAIS) by Schepman & Rodway (2020, 2023), measured by a 5-point Likert scale |

*End of Table 3*

| Author(s) | Data collection method / tool |
|---|---|
| Wang et al. (2024) | 2 items on Privacy protection (Sharma et al., 2019), 3 items on Perceived security (Sharma et al., 2019), 3 items on Perceived ethics in beneficence (Limbu et al., 2012), 3 items on Trust in chatbot (Gefen & Pavlou, 2012), 7 items on Intention to recommend chatbot (Oliveira et al., 2016); all measured by a 7-point Likert scale |
| Yang (2024) | 20-item questionnaire based on various sources (see detailed information in Appendix), measured by a 7-point Likert scale |
| Zhang (2024) | 20-item questionnaire adapted from previous reviews on performance expectancy, effort expectancy, social influence, and behavioral intention, measured by a 4-point Likert scale |
| Arora et al. (2025) | 20-item General Attitudes Toward Artificial Intelligence Scale by Schepman & Rodway (2023), measured by a 5-point Likert scale |
| Benhayoun et al. (2025) | 20-item questionnaire adapted from various sources (see detailed information in Table 1), measured by a 5-point Likert scale |
| Daly et al. (2025) | Thematic analysis, inductive research approach outlined by Gioia et al. (2013) |
| Do et al. (2025) | 11-item scale on Trust in AI adapted from Chowdhury et al. (2022), measured by a 5-point Likert scale |
| Korayim et al. (2025) | 6-item construct on Attitudes toward Generative AI adapted from Farjon et al., 2019; 4-item construct on Learning effectiveness adapted from Kankanhalli et al., 2011; both measured by a 7-point Likert scale |
| Manresa et al. (2025) | Constructs on Assess GenAI (3 items), Usefulness (3 items), Attitude toward AI (4 items), Trust in GenAI (7 items), adapted from various sources (see detailed information in Table 1), measured by a 5-point Likert scale |
| Marimon et al. (2025) | 3-item construct on Optimism, adapted from Parasuraman (2000); 4-item scale on Innovativeness adapted from Parasuraman and Colby (2015); 3-item scale on Usefulness an d 3-item scale on Easy to Use adapted from Davis (1989); 7-item scale on Trust adapted from Candrian and Scherer (2022); Frank et al. (2023); Glikson and Woolley (2020); Mayer et al. (1995); McKnight et al. (2002); measured by a 5-point Likert scale |
| Ratta et al. (2025) | UTAUT-based model with additional constructs, comprising 3 items each on performance expectancy, effort expectancy, and self-efficacy, plus 4 on perceived risk, 4 on social influence, 4 on trust, and 3 on adoption intention, all measured on a 5-point Likert scale (see Table 2) |
| Swinger et al. (2025) | Design fiction, factorial survey vignettes, video storyboard prototype, audio recording and transcription; thematic analysis |
| Tandon et al. (2025) | Gioia methodology (Gioia, Corley, and Hamilton, 2013), followed standard recommended practices for qualitative coding, proceeding in three phases of analysis (grounded theory approach) |

emerging as a dominant standard. Researchers employed a wide range of tools, from well-established and validated models such as the UTAUT and its extensions, the General Attitudes toward Artificial Intelligence Scale (GAAIS), and the Artificial Intelligence Acceptance–Avoidance Model (IAAAM), to adapted measures originating from other domains, including privacy protection, trust, and service robot integration. In several cases, scales were adapted from general technology acceptance research or domain-specific contexts, indicating an ongoing tendency to repurpose existing frameworks rather than develop AI-specific attitude measures from the ground up.

Of the analyzed measurements, the Integrated AI Acceptance–Avoidance Model (IAAAM) provides the broadest assessment of attitudes toward AI, as it incorporates the largest set of distinct constructs and the scale is consisted out of 49 items – the most among all reviewed studies. However, it is noteworthy that the IAAAM, introduced in 2021, was applied only once in the reviewed studies up to 2025, and solely in an abbreviated form.

## 4. Discussion

This systematic review is focused on how employee attitudes toward AI in the workplace are defined and measured. In doing so, it addresses an important gap in the literature by transitioning from a narrow focus on technological utility and organizational infrastructure toward a broader, more holistic, human-centered perspective (Park et al., 2024; Suseno et al., 2022). This review lays the groundwork for future conceptual clarification and methodological consistency regarding employee attitudes toward AI in the workplace.

29 reviewed studies were conducted across a wide geographical range, reflecting the global interest in employee attitudes toward AI in the workplace. The diversity of sectors represented in the research underscores how widespread AI has become in workplace settings. While many scholars call for additional studies, for example, comparing less developed or less technologically advanced countries (Tandon et al., 2025), exploring a broader range of organizational settings (Almashawreh et al., 2024), and conducting longitudinal research to observe how attitudes toward AI evolve over time (Revillod, 2024) – this review suggests that such diversity simultaneously creates a methodological challenge. Conducted review showed that the construct of attitude is defined and operationalized in varying ways across studies. Many researchers adopt a basic dichotomy of positive vs. negative attitude, however, other work extends beyond a one-dimensional view (e.g., tripartite model of attitude – distinguishing cognitive, affective, and behavioral components). Despite differences

in emphasis and the inclusion of additional sub-dimensions, a common thread is shared – attitudes toward AI are multi-dimensional, combining evaluative beliefs, affective feelings, and this nuanced understanding is seen as crucial for predicting employees' intentions to use AI and for successfully integrating AI into organizational contexts. Although historically, research largely ignored the negative emotional responses to technology (Cao et al., 2021; Suseno et al., 2022), it is now apparent that the focus is expanding. However, it has not been established which attitudes toward AI are fundamental, nor whether and how they can be differentiated into primary and secondary (i.e., less significant). Also, fragmentation of measurement practices across studies makes it challenging to compare findings and draw cumulative conclusions. The use of diverse, often study-specific instruments limits the consistency and generalizability of results. This highlights the need to develop an applicable, validated method for measuring employee attitudes toward AI in the workplace. Additionally, the limited use of qualitative or mixed-method approaches constrains the ability to capture the contextual and experiential nuances of these attitudes. Moreover, current dominance of quantitative designs restricts insights into how employee attitudes toward AI evolve over time. As AI technologies continue to advance and their workplace applications diversify, longitudinal research could track changes in attitudes, further, as well as to identify the factors that shape these attitudes. Also, it remains unclear whether measuring behavioral intention is sufficient, as it does not necessarily reflect actual or sustained use of AI in the workplace.

Although this review provides a comprehensive overview of research on employee attitudes toward AI in the workplace, certain limitations must be acknowledged. Only two databases were utilized: Scopus, selected for its comprehensive coverage of peer-reviewed literature (approximately 99% of Web of Science-indexed journals are also indexed in Scopus; Singh et al., 2021), and EBSCOhost, included to access subject-specific, practice-oriented research not typically found in citation-focused databases. Additionally, restricting the search to peer-reviewed empirical publications in English may have excluded valuable perspectives from non-English-speaking or Global South contexts, where AI adoption patterns may differ. Furthermore, although every effort was made to enhance consistency and objectivity throughout the implementation of this systematic review, some degree of bias in the analysis and interpretation of the data may still be present and cannot be completely excluded.

## 5. Conclusions

To the best of our knowledge, this systematic review is the first to provide a comprehensive synthesis of existing research on employee attitudes toward AI in the workplace, with a specific focus on how these attitudes are conceptualized and measured. The findings revealed a fragmented and inconsistent scope, with substantial variation in conceptual definitions and measurement practices across studies, further complicated by differences across organizational sectors and occupational roles. The use of diverse, often study-specific instruments limits the consistency and generalizability of results. This review highlights the need to clearly define fundamental employee attitudes toward AI in the workplace and to employ a validated method for analyzing and measuring these attitudes over time, in order to capture whether and how they change across different periods. Such an approach, applicable across industries and job roles, would facilitate comparability in future research and help organizations manage employee attitudes and take appropriate action when implementing AI.

In conducting the systematic literature review, future research could benefit from incorporating additional databases and multilingual sources to enhance coverage. Moreover, since the concept of attitude is itself rather broad, effort should be made to determine which attitudes toward AI are fundamental and how they can be classified into primary and secondary categories. Future research should prioritize the development of standardized instruments to measure employee attitudes toward AI, enabling greater comparability across different settings. Additionally, longitudinal research designs would help understand how attitudes evolve over time. Lastly, research could move beyond measuring behavioral intention to examining actual and sustained AI use in workplace settings.

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*Note*: References indicated with an asterisk (*) were included in the systematic literature review.