EPH-International Journal of Business & Management Science

FROM AUTOMATION TO RESPONSIBLE HIRING: A SYSTEMATIC REVIEW OF ARTIFICIAL INTELLIGENCE IN RECRUITMENT AND SELECTION

Dr. Shaik Kamruddin[1]

[1]*Associate Professor; Department of Management and Commerce; Maulana Azad National Urdu University (Central University), Hyderabad; Telangana 500032, India; Email: kamruddin@manuu.edu.in*

Article History
Received: *2026-03-23*
Revised: *2026-08-09*
Accepted: *2026-10-11*
Published: *2026-10-27*

Abstract
This study systematically analyses the growing body of literature that relates to artificial intelligence (AI) and its use in recruitment and selection. It aims to unify scattered evidence from human resource management, personnel psychology, information systems, business ethics, and computer science, and to identify key technologies, frameworks, methods, ethical issues, and future research directions.
This paper examines the Scopus dataset consisting of 270 journals published in the English language, as well as a robust database of 125 studies based on the use of Artificial Intelligence in recruitment and selection. A detailed metadata analysis was carried out in order to identify the major trends in publishing, stages of recruitment, technologies, research methods, theories, and behavioural and ethical issues.
The study area is on the rise, and 98 out of the 125 studies were published in the period from 2023. The most common technological features are algorithmic decision support, machine learning and résumé screening. The most dominant research themes that have been analysed in those studies are acceptance of the technology, bias/discrimination and efficiency/quality-of-hire. Fairness, trust, explainability, privacy, diversity, human–AI collaboration, and applicant reactions are among emerging concepts in the field.
The literature review will have limitations arising from its reliance on abstracts and metadata alone, and given this, some details about the particular study may not be included. Future research should feature full-text review and formal quality measures in order to ensure a stronger evidence base.
The study combines disparate evidence into the framework of responsible AI-driven recruitment and proposes a research agenda that emphasises fair audit, meaningful human governance, reproducibility of GenAI, timeline design, cross-cultural comparison, and post-hire validation.

Keywords: *Artificial Intelligence; Recruitment; Personnel Selection; Algorithmic Hiring; Machine Learning; Applicant Reactions; Fairness; Trust; Explainable AI; Generative AI; Human-AI Collaboration.*

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

1. Introduction

In recruitment and selection, artificial intelligence (AI) is steadily moving beyond the boundaries of being just an experimental support technology by becoming an increasingly visible social practice. Firms employ algorithm-based instruments to attract candidates, run advertisements, screen CVs, grade applicants, consider their assessments, run or facilitate interviews and make recommendations on hiring decisions. While the use of these applications promises fast processing, uniformity, scalability and better matching, at the same time it affects who is visible, how the evidence is interpreted, which attributes are rewarded, and how responsibility is assigned if decisions are challenged. Thus, the question is not only whether organisations should adopt specific AI in recruitment, but how to build, manage, mix with human judgment and evaluate specific AI solutions along the recruitment path.

The earlier literature focused mainly on adoption, efficiency and decision support. Pillai and Sivathanu (2020) modelled the process of organisational adoption of AI for recruitment purposes. Pessach et al. (2020) showed the great potential of machine learning and mathematical programming in making prescriptive recruitment analytics. Allal-Chérif et al. (2021) defined intelligent recruiting as the identification and selection of candidates at scale. At the same time, ethnographic and behavioural research called into question the belief that automation means waving goodbye to human expertise. For instance, Van den Broek et al. (2021) showed that AI development in recruitment turned into a hybrid practice where machine learning and expertise were interdependent rather than interchangeable. A second area of research has begun to shift the emphasis from operational value to validity. Applicant-based studies demonstrate that automated selection can affect perceptions of procedural and interactional justice, trust, organisational attractiveness, and intentions to apply or accept a verdict (Acikgoz et al., 2020; Gonzalez et al., 2022; Noble et al., 2021; Wesche & Sonderegger, 2021). Legal and critical literature also emphasised that artificial intelligence can replicate or eliminate discrimination. This is because of the impact of training data in the designs employed and the decisions made by human beings (Drage and Mackereth, 2022; Kelan, 2024; Rigotti & Fosch-Villaronga, 2024). More recent works extend these concerns to AI technology explanations, automated interviews, and LLMs, generative AI used on applicants' side, neurodiversity, and intercultural differences.

Besides widening the understanding of AI technology, these studies show that knowledge in this domain is conceptually fragmented. Technical studies deal with predictive accuracy or the results of rankings; behavioural studies look into people's attitudes and ideas related to the treatment of justice; organisational studies involve the AI adoption process; and ethical or legal studies deal with discrimination, privacy and accountability issues. Each of these universities employs different terminology and emphasises varied outcomes, which makes it difficult to say when AI becomes effective, valid, and sustainable as an organization's practice at the same time. The data collected from the Scopus database show the fragmentation of evidence between different domains of social sciences such as recruitment and assessment, HRM, psychology, information systems, legal studies, and ethical issues, with no journal being the leading one in the field.

The purpose of the current review is to overcome the fragmentation through the move from the simple inventory of technologies to the consideration of the ways AI and human governance influence recruitment outcomes. The authors use principles of systematic review (Snyder, 2019; Tranfield et al., 2003) and the principles of reporting new empirical studies developed by PRISMA 2020 (Page et al., 2021) to create a map of evidence, define the dominant and underdeveloped themes and create an integrated research agenda. It is evident that the research has highlighted three primary tensions affecting the research process: efficiency vs. legitimacy, automation vs. human agency and standardisation vs. fairness, which can provide a theoretically defined basis for future studies on the AI recruitment phenomenon.

1.1 Review Objectives and Research Questions

The review has five objectives: to map the growth and disciplinary dispersion of AI recruitment research; identify the recruitment stages and AI technologies receiving most attention; assess the theoretical and methodological profile of the field; synthesise dominant ethical, behavioural, and organisational mechanisms; and translate corpus-level gaps into a future research agenda.

RQ1. How has research on artificial intelligence in recruitment and selection evolved over time and across source journals?

RQ2. Which stages of recruitment and selection and which AI technologies receive the greatest scholarly attention?

RQ3. Which theoretical perspectives, research designs, and analytical methods are most frequently used?

RQ4. Which ethical, behavioural, and organisational mechanisms dominate the literature, particularly fairness, bias, trust, explainability, privacy, human-AI collaboration, and applicant reactions?

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

RQ5. What theoretical, methodological, technological, contextual, and measurement gaps provide the strongest directions for future research?

1.2 Contribution of the Review

This study is useful for three reasons. First, it offers a current evidence map in rapidly growing literature, which identifies recruitment stages, types of technology used, and research methods with respect to the role of applicants and organisations in the outcomes. Second, the findings are integrated into three general tensions, and a responsible AI recruitment framework is proposed, which shows how different features of systems and governance configurations influence outcomes through psychology and legitimacy. Finally, the study proposes a design-oriented research agenda that will connect future inquiries and empirical strategies in the scope of the project, such as field trials, longitudinal studies, audits of fairness, analyses of various groups, cross-country comparisons, validation of hired people, etc.

2. Review Methodology

The review is conducted in accordance with a well-structured management review approach and the principles of transparent and reproducible evidence synthesis (Snyder, 2019; Tranfield et al., 2003). In order to ensure transparency in terms of identification and screening, PRISMA 2020 is adopted as the reporting reference (Page et al., 2021). Nevertheless, the uploaded source contains only Scopus metadata and abstracts, but not the actual full text; therefore, it is necessary to classify the review as a systematic literature review and evidence map at the metadata/abstract level, whereas the formal claim for completed PRISMA full-text eligibility can be made only after the completion of full-text retrieval and exclusion recording.

2.1 Database, Identification Set, and Screening

The evidence base is the uploaded Scopus CSV export made up of 270 English-language journal articles. The export contains neither duplicate titles nor duplicate DOI numbers. The record was sorted into three different groups using the title-keyword-abstract screening protocol used in this study: 125 studies strongly oriented towards procurement or selection, 131 related or ancillary studies which, as a rule, have a signal of joint AI and recruitment, and 14 irrelevant studies. The quantitative analysis of the manuscript is based on the high-confidence corpus of 125 studies.

Table 1. Review dataset profile

Indicator	Value	Interpretation
Records in Scopus identification set	270	Identification set
Duplicate titles / DOI duplicates	0 / 0	No duplicates detected
High-confidence analytical corpus	125	Direct AI-recruitment/selection relevance
Supplementary / adjacent pool	131	Broader or weaker focal relevance
Low-relevance / non-core records	14	Not retained in core synthesis
Core records with DOI	124	99.2% DOI coverage
Core Scopus citations	5,248	At export date
Core dataset h-index	33	Based on Scopus 'Cited by' values

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

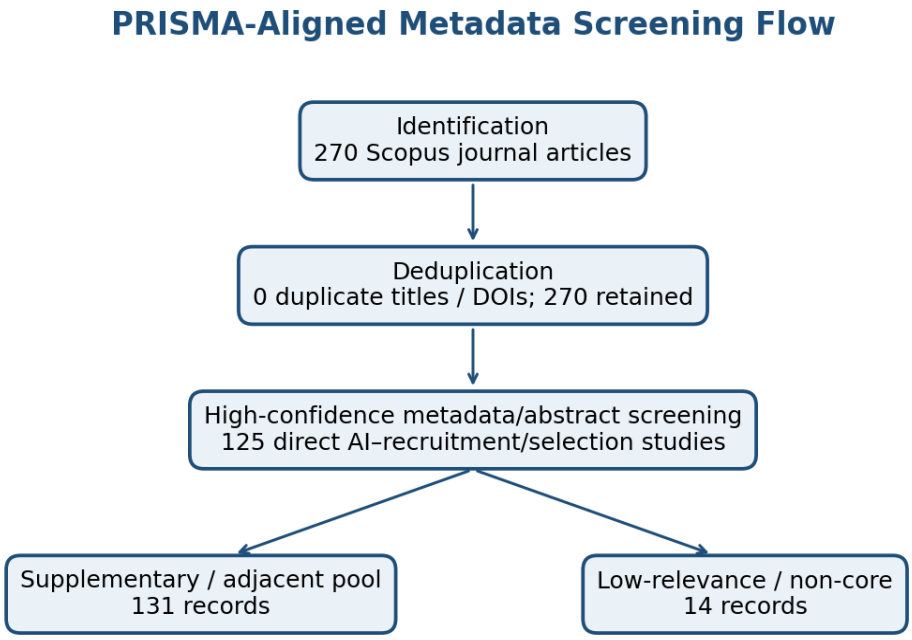


Figure 1. PRISMA-aligned metadata and abstract screening flow for the uploaded Scopus export.

The precise Scopus Advanced Search query is missing from the CSV file uploaded. Thus, this paper does not recreate and show an estimated search expression as if it were the original search code. Before submission, the TITLE-ABS-KEY search phrase, date of the search, and filters need to be copied from Scopus Search History. This limitation does not influence the descriptive statistics provided based on the export that has been uploaded.

2.2 Eligibility Logic

Table 2. Eligibility and screening logic

Decision	Criterion	Operational interpretation
Include	AI is used, evaluated, governed, or perceived as part of recruitment, talent acquisition, screening, assessment, interviewing, or personnel selection.	Direct title/keyword/abstract evidence
Include	Empirical, conceptual, technical, legal/ethical, review, or methodological journal articles directly addressing AI-mediated recruitment/selection.	All identification records were journal articles
Exclude from core	Studies about recruiting AI talent, labor-demand forecasting, or job-market analytics where AI is the object of hiring rather than the recruitment technology.	May remain in adjacent pool
Exclude from core	General HRM/AI studies where recruitment is incidental, or technical papers unrelated to employee recruitment/selection.	Not used in core quantitative synthesis
Full-text requirement	Sample frames, measures, model specifications, exclusion reasons, and risk-of-bias judgments require full-text validation.	Essential before final journal submission

2.3 Coding and Synthesis

The 125 key studies were assessed using titles, abstracts, and author keywords according to a multi-label scheme, thus allowing one article to contribute analytically to several recruitment stages, technologies, methods, theories, or constructs. That is why the percentages shouldn't be summed up to reach 100%. The dimensions coded included the recruitment stage, type of the AI technology or system, a theoretical framework mentioned in explicit terms, research design and analysis method, author-affiliation country, sector or organisation context, and dominant constructs such as adoption, bias, fairness, trust, explainability, privacy,

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

diversity, reactions of the applicants, and human-AI collaboration. Citation counts and h-index values depict the date of the Scopus export being done.

The synthesis was conducted in two steps. The first step is descriptive and reflects the setup of this area. The second step is interpretive, in which the comparison between the results of different technical, behavioural, organisational, and ethical streams of thought has been made to identify repeating issues and engines. There has been no statistical meta-analysis since the corpus covers heterogeneous technologies, results, types of research, and units of analysis. Instead, thematic integration and theory-led interpretation methods are employed in this review to develop a future research agenda.

2.4 Review Quality and Boundary of Inference

The corpus boasts robust bibliographic traceability, with 124 out of the 125 core studies having a DOI; however, at the level of the abstract, reporting seems inconsistent. Only 21 studies from the pool of examined studies have explicitly referred to any of the coded theories in their title, abstract, or keywords, whereas the details of the design and sample, study scale, and mode version are frequently absent from their abstract. As a result, the study does not assign any risk-of-bias score, nor does it assume that a metadata field that is empty means that the study did not have a certain construct/theory. All claims about novelty or innovation have been made on the corpus level, not globally.

3. Descriptive Structure of the Field

3.1 Publication Growth and Journal Dispersion

The progress in this area is very recent. Of the 125 studies, 98 (78.4%) were published in or after 2023. The volume of publications grew from just 11 studies published in 2022 to 16 in 2023, 28 in 2024, 23 in 2025, and 29 in 2026 (which is still ongoing). The two references marked 2027 should be treated as metadata about future years and not as a full count for that year. The increased volume shows a significant interest in the field, which brings some level of uncertainty as new technologies are introduced more quickly than theory can be developed.

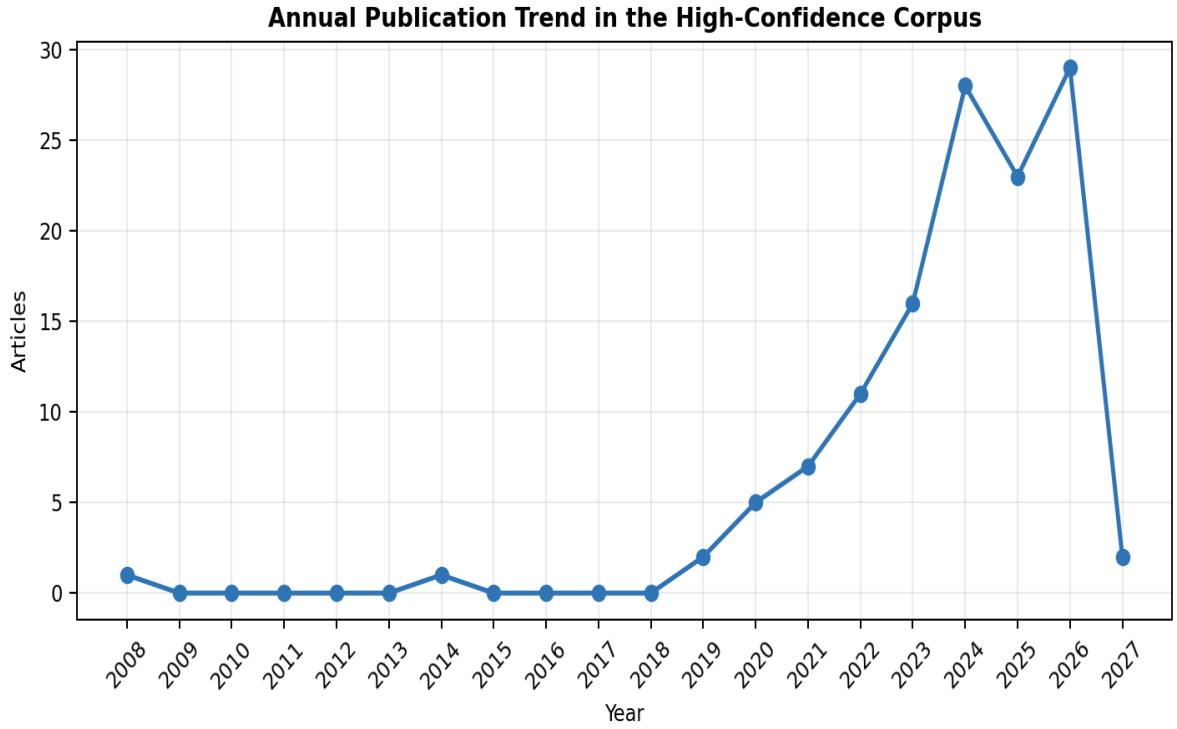


Figure 2. Annual publication trend in the high-confidence AI recruitment and selection corpus.

Literature also varies by institution. Although the International Journal of Selection and Assessment published the most studies, these studies have been published in separate journals that focus on subjects such as human resource management, psychology, information systems, technology, business ethics, and decision support. This provides an understanding of why the field of study is complicated due to the presence of multiple terms for the same idea.

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

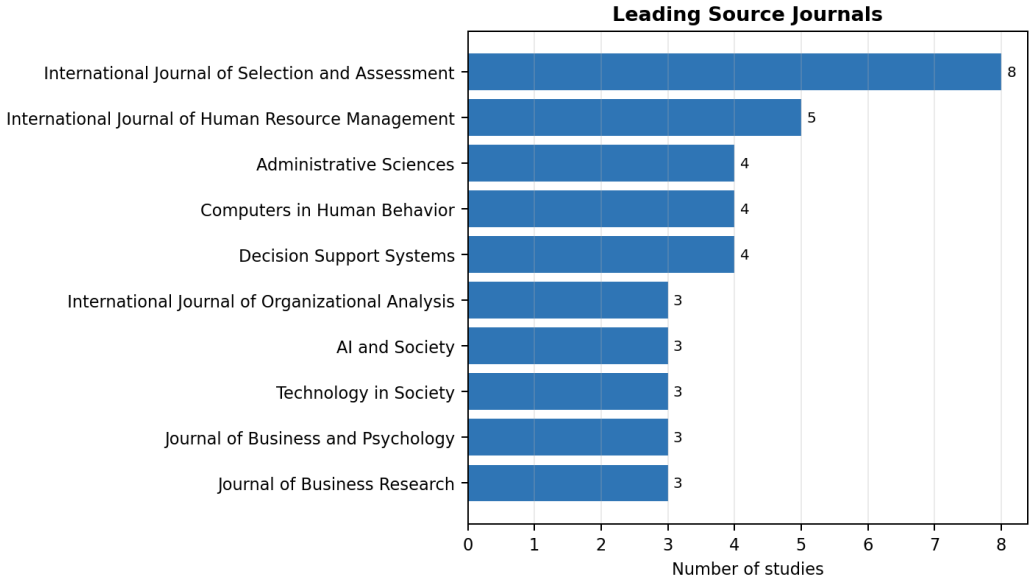


Figure 3. Leading source journals in the high-confidence corpus.

3.2 Recruitment Stages and AI Technologies

The utilisation of artificial intelligence is not confined to just one function of the recruitment process. The largest number of studies focused on sourcing and attraction at 65 research articles, followed closely by 51 articles on end-to-end talent acquisition and 50 articles that deal with decisions of selection or hiring. Also, 34 studies focused on the interviewing process, followed by the studies of screening (29) and assessment/testing, which received 28 studies overall. This number is significant as it helps to determine the expectation of the candidates at different stages.

Table 3. Recruitment stages represented in the core corpus

Recruitment / selection stage	Studies	% of core
Sourcing / attraction / job advertising	65	52.0
Talent acquisition / end-to-end recruitment	51	40.8
Selection / hiring decision	50	40.0
Interviewing	34	27.2
Screening / pre-selection / resume review	29	23.2
Assessment / testing	28	22.4

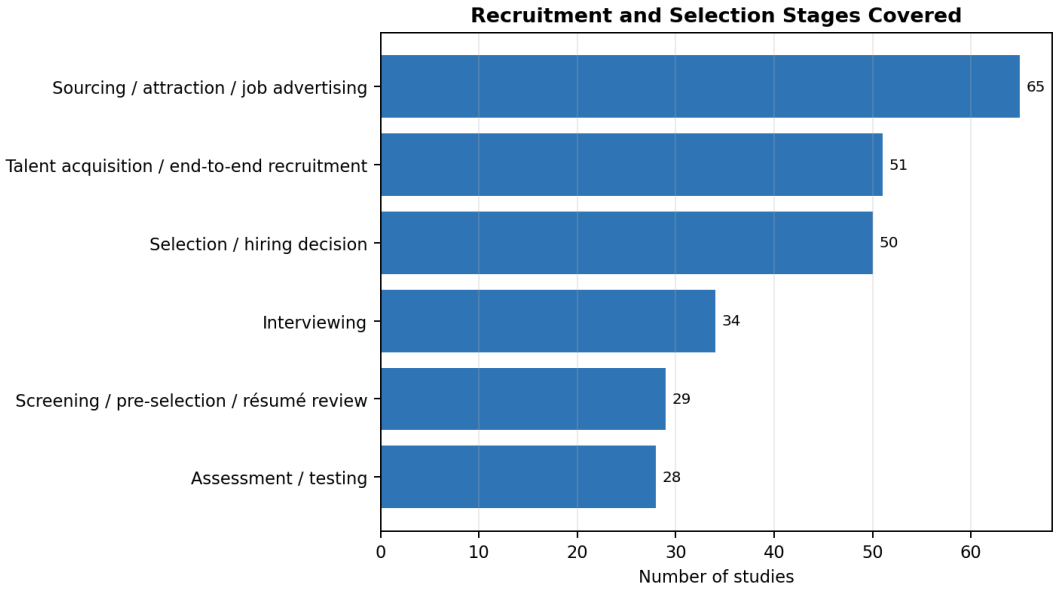


Figure 4. Recruitment and selection stages covered in the core corpus.

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

The technology profile is moderately heterogeneous. The most dominant category includes broad algorithmic or automated decision support (53 studies), followed by machine learning or predictive modelling (35 studies), and resume/CV screening/matching (23). Explainable AI and NLP/LLM/Generative AI appear in 18 studies each, while automated interviews and conversational agents appear in 11. Social-media screening or cybervetting is relatively uncommon. This combination of patterns reinforces the necessity of moving forward with various independent variables rather than just the generic one "AI use," such as the type of system, task, level of autonomy, input data, and extent of human review.

Table 4. AI technologies and system types

Technology/system type	Studies	% of core
Algorithmic/automated decision support	53	42.4
Machine learning / predictive modelling	35	28.0
Resume/CV screening and matching	23	18.4
Explainable AI (XAI) / transparency	18	14.4
NLP / LLM / Generative AI	18	14.4
Automated / AI interviews	11	8.8
Chatbots / conversational agents	11	8.8
Social-media screening / cybervetting	2	1.6

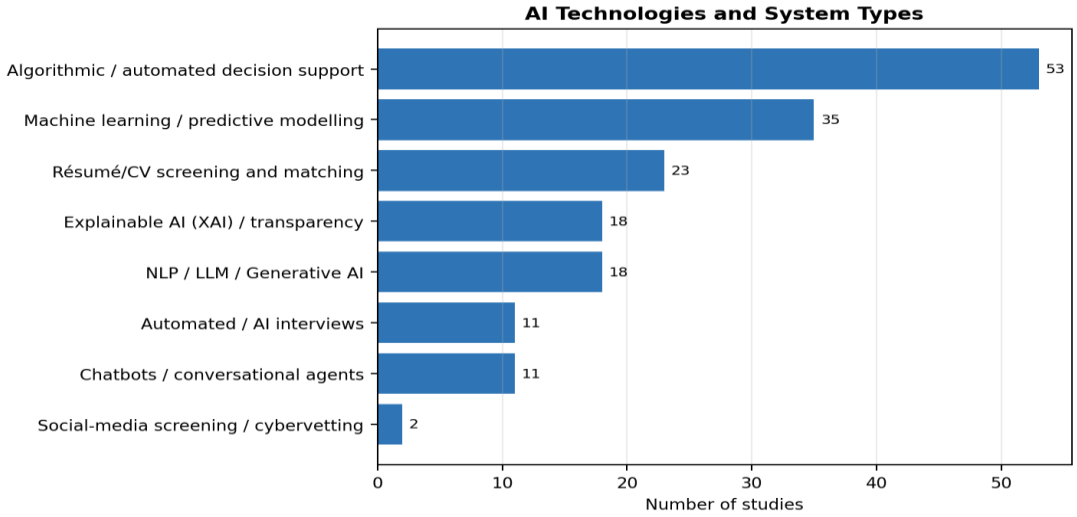


Figure 5. Most frequently identified AI technologies and system types.

3.3 Theoretical and Methodological Profile

Theory development hasn't kept up with empirical and technological advances. Just 21 out of 125 core studies use one of the theoretical frameworks coded in their metadata or abstracts. The most common framework in the studies that mention it is Organisational or Procedural Justice (6 studies), followed by Sociomaterial or Sociotechnical frameworks (5 studies) and UTAUT (4 studies). Person-environment fit, Signalling Theory, and TAM only make up 2 studies. The low explicit mention of theory proves that the complete texts are not theory-driven, but it indicates that the field is mainly structured around technologies and problems..

Table 5. Dominant theoretical frameworks and research methods

Theory/framework	Studies	Method/technique	Studies
Organizational/procedural justice	6	Experiment / vignette / scenario	28
Sociomaterial / sociotechnical perspective	5	Survey/questionnaire	21
UTAUT / unified technology acceptance	4	Qualitative/ethnographic / research interviews	14
Person-environment / person-organisation fit	2	SEM / PLS-SEM	9
Signaling theory	2	Case study / multiple case study	7

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

Technology Acceptance Model (TAM)	2	Systematic literature review	5
Applicant attribution/attribution theory	1	Technical model evaluation / benchmark	5
Diffusion of innovation	1	AHP / MCDM	3
Fairness heuristic theory	1	Mixed methods	3
Resource-based view	1	Regression / econometric analysis	3
		Bibliometric analysis	2
		Conjoint / discrete-choice design	1

Methodologically speaking, the field is more pluralistic. Experiments, vignettes or scenarios stand out as the most frequently used designs (28 studies), further supported by surveys conducted in 21 studies, and qualitative/ethnographic/research-interview approaches embraced in 14 studies. SEM/PLS-SEM can be found in 9 studies while case studies are used in 7 and technical benchmarks in 5 studies. Such diversity is a benefit because recruitment by AI contains both system's actions and applicants' reactions. However, it has a disadvantage. These two angles are usually studied independently: technical studies focus on effectiveness of algorithms, whereas behavioral studies pay attention to perception only. Longitudinal evidences which connect system's characteristics, applicants' behavior, hiring decisions, harm done to segments of the population, and job success are rather limited.

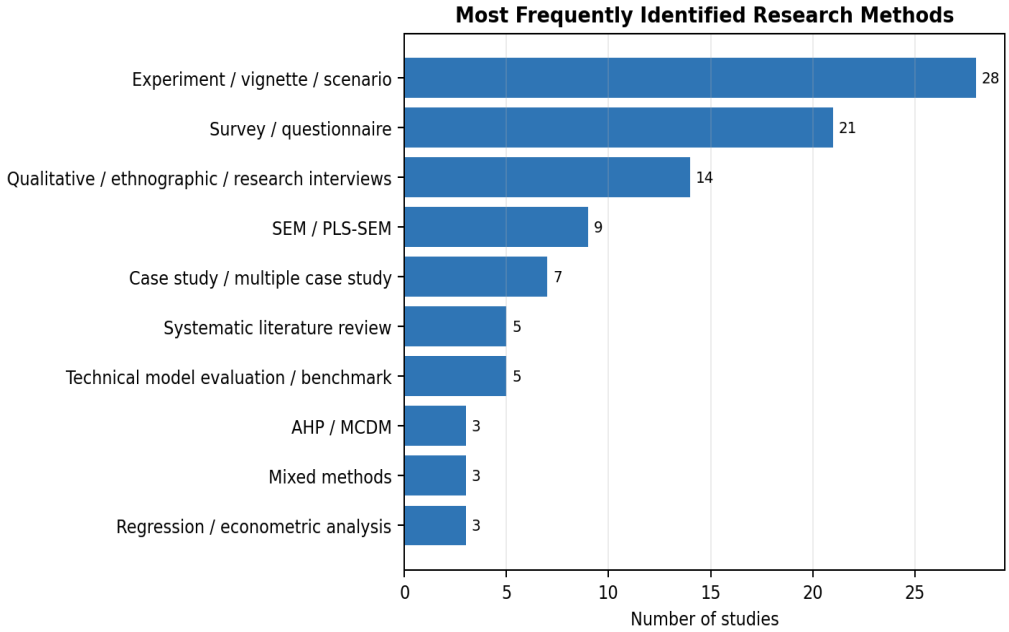


Figure 6. Most frequently identified research methods and analytical approaches.

3.4 Geographic and Sector Context

The origins of the authors indicate a global interest in the topic, particularly in the United States (27 studies), India (19), Germany (16), and the United Kingdom (12). The numbers here pertain to the places where the studies were carried out rather than the locations of the fields of research. Among the explicitly stated segments, higher education is the biggest segment (14), followed by hospitality/tourism/events (8), manufacturing (7), IT/software/digital firms (6), healthcare (5), and the public sector (5). The majority of the studies are cross-sectoral or generic HR/recruitment studies.

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

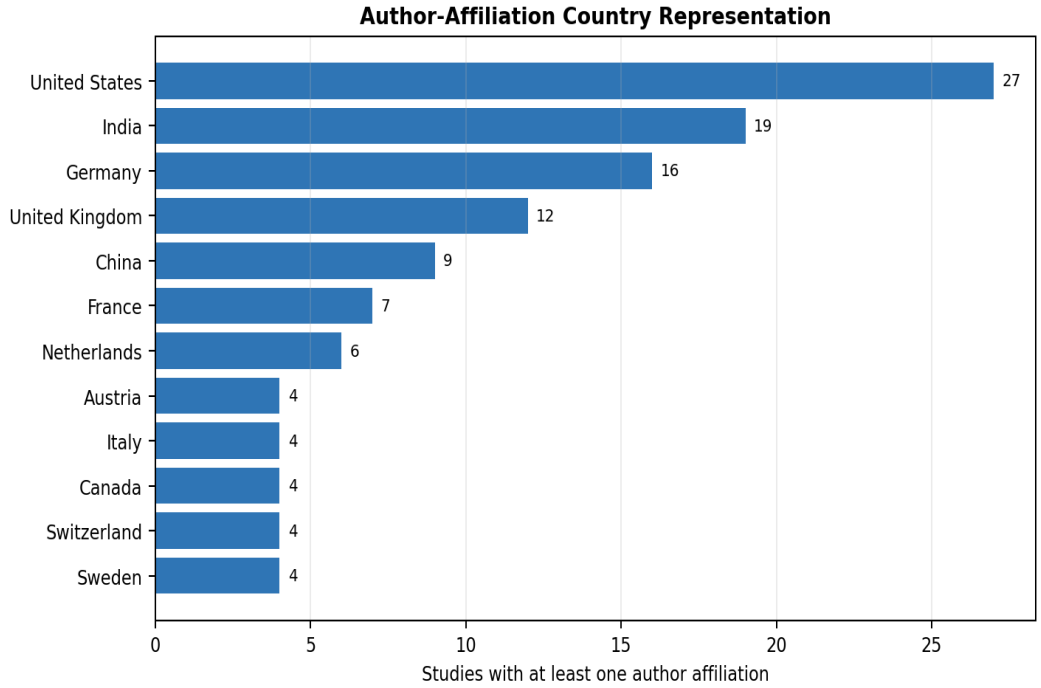


Figure 7. Leading author-affiliation countries in the core corpus.

4. Thematic Synthesis: From Fragmented Findings to Three Organising Tensions

The descriptive results reveal what the different studies in the field have been concerned with, but the question is how they connect with each other. The studies, which seem to be different from each other, are actually connected by three tensions throughout the corpus. The first is efficiency and legitimacy; systems can be efficient in terms of speed, consistency, or predictive accuracy, but at the same time make the process less fair and less private and violate the dignity of the candidates. The second tension is between automation and human involvement; organisations want to be automated but still need human involvement in terms of judgment, control, interpretation, or responsibility. As for the third tension, it is between standardisation and contextual fairness; on the one hand, algorithms ensure consistency and eliminate many subjective components of work, but, on the other hand, they can give rise to new problems in cases when data, categories, explanations, or interfaces do not match the particular group, stage, job, or place.

4.1 Tension 1: Efficiency Versus Legitimacy

The themes of efficiency and quality of hire rank as the most prevalent in the corpus of studies analysed in the present article, appearing in 39 instances. This instrumental focus is reflected in several areas of research concerning the adoption of AI, its ranking, predictive modelling, and decision support. Pillai and Sivathanu (2020) assert that the degree of perceived relative advantage, cost-effectiveness, readiness of the organisation, as well as support from top management and vendors, influence their willingness to adopt AI in talent acquisition, while Pan et al. (2022) point out that technological complications and competence of the organisation in using technologies are important for the adoption of AI. Technical research findings (Pessach et al., 2020; Tian et al., 2023; Thompson et al., 2023) suggest ways machine learning can support recruitment optimisation, processing resumes, and scoring candidates automatically.

Nonetheless, efficiency enhancements alone cannot guarantee effective legitimacy. Fairness/justice are present in 22 studies, bias/discrimination in 39 studies, privacy/surveillance in 14 studies, and diversity/inclusion/accessibility in 24 studies. The experiments centred around the candidates reveal that AI-based selection is often seen as less just than human-based selection, especially in cases where parts of communication, reconsideration, job relevance, or interpersonal treatment lack effectiveness (Acikgoz et al., 2020; Noble et al., 2021). It is also essential to mention the effect of favourable outcomes: Bedemariam and Wessel (2023) note that having been rejected by AI has a worsening impact on perceptions of justice, with the findings being different across racial groups. These findings reveal that performance of the system and legitimacy of the candidates are not the same concepts and can actually move in different directions.

This discrepancy has important theoretical implications because justice refers to the perceived fairness of treatment and process (Colquitt, 2001; Gilliland, 1993), while adoption studies usually highlight the importance of usefulness, suitability, and readiness to adopt new technology. Therefore, a quality research agenda should

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

not involve models in which "effectiveness of AI" is measured by the single outcome. At least one outcome of the efficiency-type (e.g. predictive effectiveness, processing time, quality of hire) and one measurement of legitimacy (e.g. process-related fairness, trust, company attractiveness, resignation, or adverse impact) should be measured in the research.

4.2 Tension 2: Automation Versus Human Agency

The second tension regards whether AI should take over, assist, or be controlled by people in decision-making roles. Van den Broek et al. (2021) provide a vital alternative to replacement theories, in that their research regarding the building of AI for recruitment highlights how developers and specialists arrived at hybrid practices thanks to continuous learning from each other. Gonzalez et al. (2022) also provide evidence that applicants view augmented or human-based methods more positively than AI methods, depending on their familiarity with the technology and the recruitment process stage. Langer et al. (2021) find out that automation changes the nature of managers' selections; Chen summarises the collaboration between recruiters and technology as a way to lessen bias.

Going through the study, 20 research articles were identified, with the code of human-AI interaction or augmentation. However, the term "human involvement" is not specific enough. Human oversight may mean nominal review, necessary confirmation, discretionary override, explaining to applicants, exception handling, bias auditing, etc. These variations may likely result in various degrees of trust, accountability, and control. The essential problem of governance is not who takes part but who decides and when, or what information is available.

The notion of trust is crucial here. The research on trust in automation shows that we can rely on algorithms given both their properties and context (Lee & See, 2004). Inside the recruitment literature, Langer et al. (2023) proved that trust spreads differently in cases where applicants interact with humans and algorithms in the presence of systematic error, while Hu et al. (2024) introduced the notion of a "trust divide" between recruiters and applicants. Thus, organisations may create a situation where AI use is accepted on the internal level while rejected by applicants.

4.3 Tension 3: Standardisation Versus Contextual Fairness

The use of AI is often considered to strengthen the principles of the organization in the development of organisations by preventing the risk of introducing personal errors into decisions. However, this does not guarantee fairness. As noted by Drage et al. (2022), "debiasing" does not exclude the case when AI maintains discriminatory classifications of both race and gender, just as Kelan (2024) argues that data, design, and decisions have to be taken together in the context of analyses of algorithmic inclusion. Hofeditz et al. (2022) claim that AI recommendations may result in eliminating certain forms of discrimination, but may also have different effects depending on the analysed demographic group; besides, their study showed that explainability intervention is not always effective. Rigotti et al. (2024) underline that fairness may have different meanings when it comes to legal, technical and organisational stakeholders.

This contextual problem is particularly pronounced in the case of people whose behaviour or communication does not correspond to standard training data. This new corpus presupposes the inclusion of explicit works on disability justice and neurodiversity in addition to the areas described above, which allows us to conclude that accessibility should not be viewed as a secondary aspect of compliance. It also concerns culture. Park et al. (2025) compare the perceptions of the justice of AI-based interviewing in the US and South Korea, while Tursunbayeva et al. (2026) demonstrate that attitudes toward AI and its input differ depending on prospective employers' backgrounds. Therefore, a universal fairness effect is unlikely, and fairness should be treated as a characteristic of a system in a certain context.

5. Core Thematic Streams

Table 6. Leading ethical, behavioural, and organisational themes

Theme	Studies	% of core
Acceptance/adoption/intention to use	39	31.2
Bias/discrimination / adverse impact	39	31.2
Efficiency/productivity/quality of hire	39	31.2
Diversity/inclusion/accessibility	24	19.2
Fairness/justice	22	17.6
Human-AI collaboration/augmentation	20	16.0

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

Transparency/explainability	18	14.4
Trust/credibility	18	14.4
Applicant reactions/candidate experience	14	11.2
Privacy / surveillance	14	11.2
Organizational attractiveness / intention to apply	6	4.8
Algorithm aversion / appreciation	4	3.2
Perceived usefulness / performance expectancy	4	3.2
Satisfaction	4	3.2

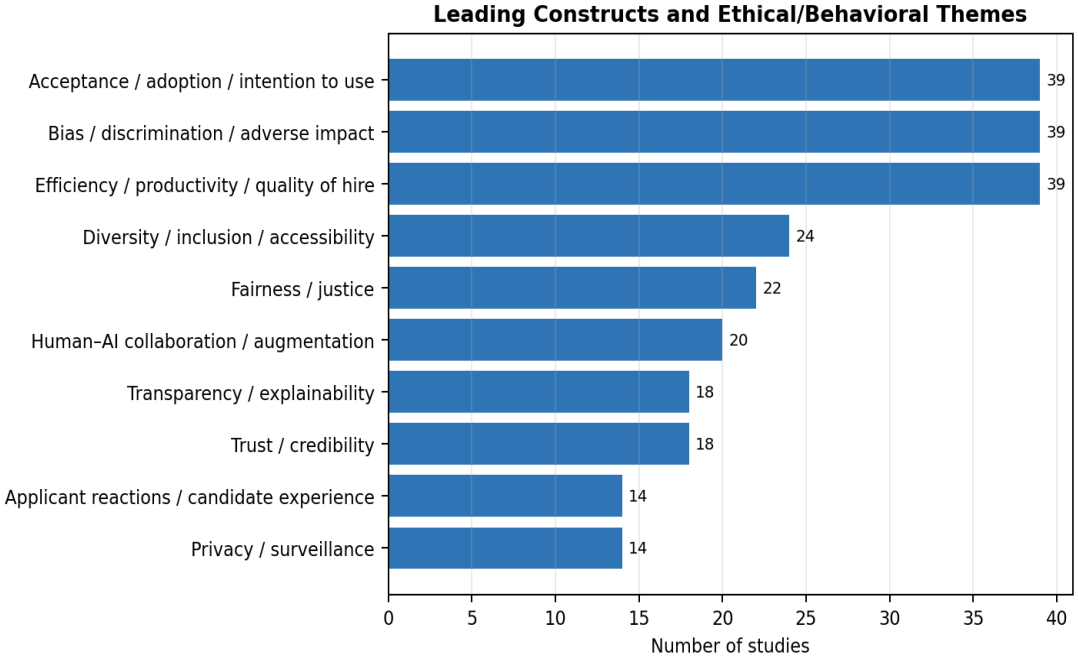


Figure 8. Leading constructs and ethical/behavioral themes in the core corpus.

5.1 Adoption and Acceptance

The concept of acceptance, use or willingness to act has appeared in 39 studies. Existing literature is derived from the concepts of organisational adoption models, technology acceptance approaches, and views of users. The Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology have introduced concepts related to perceived usefulness, perceived ease of use or social influences (Davis, 1989; Venkatesh et al., 2003), nevertheless, the issue of legitimacy connected with AI recruitment must be taken into account: while the technology could facilitate the work of the employer, it may not be acceptable to the applicant. Although in their work Pillai and Sivathanu (2020) and Pan et al. (2022) essentially address the problems of organisational adoption Amanda van Esch et al. (2019), Wesche and Sonderegger (2021) and Figueroa-Armijos et al. (2023) demonstrate a more direct approach concentrating on the attitudes of candidates and their intentions. These approaches should be considered jointly and not separately.

5.2 Fairness, Bias, and Inclusion

Discrimination and bias are among the three main concepts presented in the corpus, even though the term "fairness" presents a large variety of possible interpretations. It may refer to the following constructs: statistical parity, subgroup error rates, adverse impact, procedural justice, equality of opportunity, fairness in interpersonal aspects, and perceived legitimacy. The emergence of these different representations of fairness leads to the construct-alignment issue. Thus, while one study may establish that an AI model minimises a particular statistical discrepancy, applicants might perceive the procedure as unfair, or the perception of fairness may change, with adverse impact on the subgroup. According to the results of Dargnies et al. (2024), greater transparency does not eliminate algorithm aversion. Based on the evidence gained, it is necessary to report not only technical fairness metrics and perceptions of fairness, but also to identify the transparency metric that is used in each particular study.

Considerably more advanced works focus on beyond-bias concepts. Here, it is possible to cite work by Frissen et al. (2023), who apply machine learning for detecting biased messages contained in job advertising; Landers

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

et al. (2023), who explore the effects of combining machine learning techniques undertaken; and Kelan (2024), whose research is focused on inclusion, which can be approached from the perspective of data, design, and decision aspects.

5.3 Explainability, Transparency, and Trust

The concepts of explainability/transparency and trust involve a total of 18 studies to date. However, the relationship between these two concepts is complex. On one hand, explanations can promote understanding. On the other hand, they can highlight problematic usage of data, lead to information overload, or fail to resolve the fear after receiving an unfavourable decision. Hofeditz et al. (2022) confirm that the effect of XAI can vary in different demographic contexts, and Fleiß et al. (2024) conclude that XAI can be used in personalised recruiting. Dargnies et al. (2024), in addition to that, provide a useful insight: people can request more detailed information regarding the algorithm, and they can still reject it, which indicates that this can depend on several variables, such as the type of explanation, timing, consequence of the decision, task, and applicant AI literacy. Apart from that, the concept of trust needs clarification. Deriu et al. (2024) show that applicants' perception of AI evaluators is lower than that of human evaluators, which affects their acceptance intentions. Also, Hu et al. (2024) demonstrate that recruiters and candidates may form different evaluations of the identical decision-making mode. Thus, trust should be regarded as an assessment of competence, benevolence, consistency of the process, and controllability instead of an instant response to the term "AI."

5.4 Applicant Reactions and Employer Signalling

Study of recruitment behaviour is pivotal because recruitment plays both an assessment role and an organisational signalling role. According to signalling theory, candidates derive characteristics of an organisation based on how the recruitment process is designed and communicated (Spence, 1973). Within the context of artificial intelligence, telling applicants about the use of automation, data, and human involvement can signal not just innovation and efficiency but also distance, surveillance, or disrespect. Van Esch et al. (2019) show that positive attitudes toward AI recruitment result in a higher probability of applying, whereas Wesche and Sonderegger (2021) show that people have negative expectations about recruitment processes if they are automated. Acikgoz et al. (2020) and Noble et al. (2021) establish fairness perceptions as a mediator in the relationship between automation and candidate behaviour.

The most logical next step is to move from stated opinions to behavioural actions. The researchers have conducted many studies about acceptance and affection, trust and satisfaction, but little attention has been paid to candidates withdrawing from the process, declining the offer, or changing their self-presentation after hiring. A behavioural research program should connect AI design with candidate behaviour at different recruitment stages.

5.5 Automated Interviews and the Sociality of AI

Automated interviewing as an area of study is unique since the system not only supports or makes decisions but also provides a platform for interaction. The works of Suen & Hung (2024) show that the use of various artificial intelligence (AI) systems in asynchronous video interviews can create differences in behaviours with respect to honesty and deception. The research conducted by Clavel et al. (2025) indicates that social factors (like intimacy behaviour) can influence the interaction with a virtual AI interviewer. On the other hand, Park & Jung (2025) prove that cultural differences affect innovativeness. These findings present an argument against purely technical models of interview automation since the interaction experience, warmth, competence, reciprocity and social presence also become important elements of the selection process.

A further complication comes from the fact that AI is used by applicants. Canagasuriam & Lukacik (2025) provide an example of ChatGPT-assisted responses that can enhance the quality of interview responses but diminish the perception of honesty and procedural justice. In this way, GenAI is used by both the employer side and by the applicant side: AI is utilised by employers to assess candidates, and applicants use AI for preparation, writing and responding. Therefore, research methods must evolve in order to reflect the complexity of recruitment and therefore treat it as a type of human-AI interaction rather than one-sided automated selection process.

5.6 Generative AI and LLM-Enabled Recruitment

NLP/LLM/Generative AI is presented in eighteen key reports. The growing significance of this concept is demonstrated by eight domains of study. The pieces of evidence introduced by the authors may cover resume automation, job ad generation, job ad assessment, helping candidates, helping at interviews, and job ad assessment. Recent studies include fine-tuning LLMs for resume analysis (Liu & Su, 2026), gender bias

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

analysis of ChatGPT in recruitment (Sivakaminathan & Musi, 2026), assessing GenAI hiring against responsible AI principles (Kwok et al., 2026), and reporting job ad evaluation problems related to race and gender disparities (Kim et al., 2026).

The GenAI concept results in a methodological problem related to results validity that previous studies in the area of algorithmic recruitment did not encounter to the same extent. Consequently, future experiments conducted in the domain of GenAI recruitment should treat the model configuration as part of the methodology section, report the model version and date, keep records of the presented prompts, carry out stability tests through repeated trials, and differentiate between the uses of the employer and the applicant.

6. Influential Studies and Intellectual Anchors

Citation counts can provide guidance in understanding which studies have shaped the language and questions of the field. The most cited core studies cover adoption, socio-technical process, applicants' response, prescriptive analytics, justice, ethics, and human-AI collaboration.

Table 7. Ten most-cited studies in the high-confidence corpus

Study	Title	Journal	Citations
Pillai (2020)	Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organisations	Benchmarking	376
van den Broek et al. (2021)	When the machine meets the expert: An ethnography of developing AI for hiring	MIS Quarterly: Management Information Systems	375
van Esch et al. (2019)	Marketing AI recruitment: The next phase in job application and selection	Computers in Human Behaviour	351
Pan et al. (2022)	The adoption of artificial intelligence in employee recruitment: The influence of contextual factors	International Journal of Human Resource Management	327
Pessach et al. (2020)	Employee recruitment: A prescriptive analytics approach via machine learning and mathematical programming	Decision Support Systems	267
Allal-Chérif et al. (2021)	Intelligent recruitment: How to identify, select, and retain talents from around the world using artificial intelligence	Technological Forecasting and Social Change	261
Acikgoz et al. (2020)	Justice perceptions of artificial intelligence in selection	International Journal of Selection and Assessment	209
Johnson et al. (2020)	The benefits of eHRM and AI for talent acquisition	Journal of Tourism Futures	165
Figueroa-Armijos et al. (2023)	Ethical Perceptions of AI in Hiring and Organisational Trust: The Role of Performance Expectancy and Social Influence	Journal of Business Ethics	140
Gonzalez et al. (2022)	Allying with AI? Reactions toward human-based, AI/ML-based, and augmented hiring processes	Computers in Human Behaviour	131

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

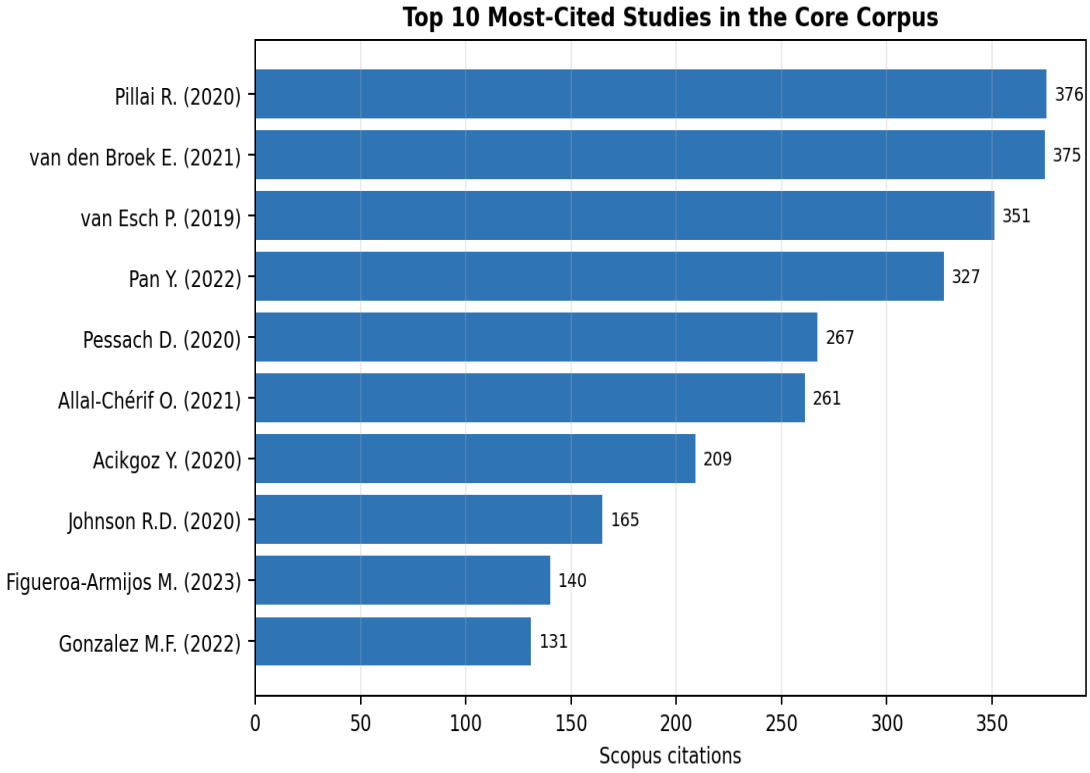


Figure 9. Top 10 most-cited studies in the high-confidence corpus.

According to the citation analysis, the existing research revolves around a few fundamental questions: what prompts organizations to utilize AI (Pillai and Sivathanu, 2020; Pan et al., 2022), how does AI affect the performance of professionals in their job (van den Broek et al., 2021), in what ways does AI impact the behavior of users (van Esch et al., 2019), how analytics helps enhance the recruitment process (Pessach et al., 2020), how applicants perceive AI-based selection process (Acikgoz et al., 2020), and finally, what criteria to use while assessing fairness, trustworthiness, and legitimacy of AI within organizations (Figueroa-Armijos et al., 2023; Rigotti & Fosch-Villaronga, 2024). The new literature seeks to develop the previous findings.

7. An Integrative Framework for Responsible AI Recruitment

The study shows that an integrative framework with three analytical levels is feasible. The first level is the design of the AI system and its governance, such as what level of automation the system has, which kind of predictive model it uses, the explainability of the model and its transparency, the scope of the data, the system features, and the rights of a human to make decisions. The second level consists of psychological and governance mechanisms, such as procedural justice, trust, perceived human control, concerns about privacy and bias, effectiveness, and interactions. The third level is related to the applicant's and organization's results, involving application and withdrawal behavior, acceptance of selection, organizational attractiveness, satisfaction, decision quality, diversity, efficiency, and post-hire results. There are also different factors, such as the phase of recruitment, level of success of the outcome, AI literacy and demographic, sector, countries and regulations in question.

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

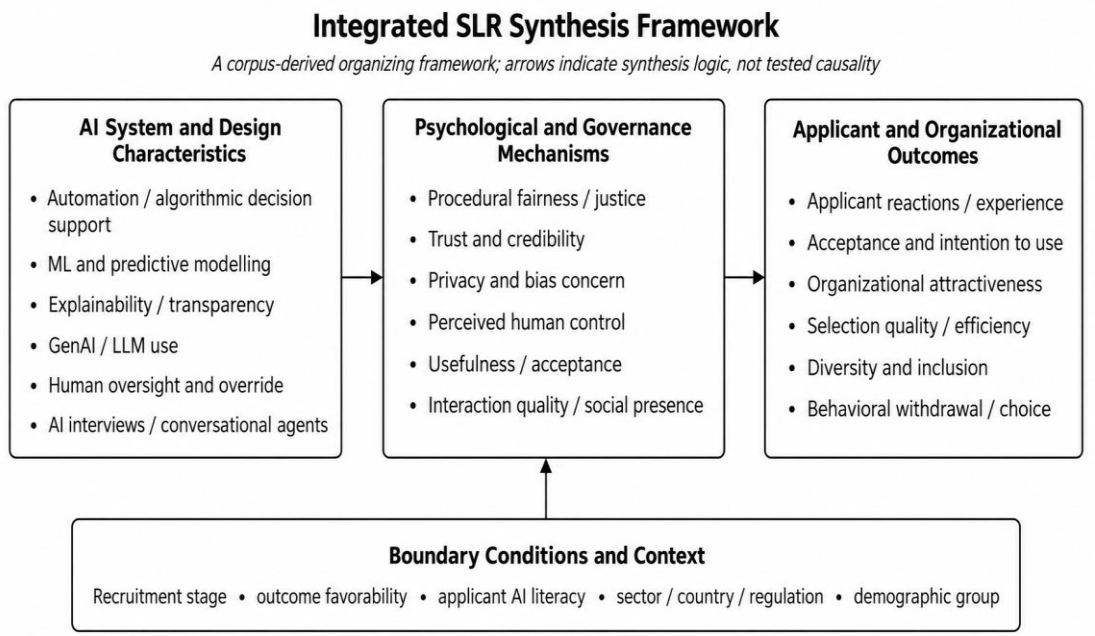


Figure 10. Integrative SLR synthesis framework for AI-enabled recruitment and selection

The framework provides two theoretical assumptions. First of all, AI would have an indirect effect: the AI characteristics affect how applicants and recruiters evaluate the process, which in turn affects their behavior. Second, governance must be considered as a part of technology effect, which means that a single predictive model can lead to somewhat different outcomes depending on who has the authority to override the model, what explanations are offered, and whether the necessary data are shared or not. For this reason, the subsequent research needs to focus on AI-human configurations instead of regarding automation as either an automatic or manual.

The framework is also useful in terms of explaining relations between different tensions. Efficiency vs. legitimacy refers to the need to evaluate the process simultaneously from the performance and from the fairness/trust perspective. The tension between automation and human agency can be expressed through contribution of human monitoring and decision-making power. Standardization vs. contextual fairness can be expressed through boundary conditions and subgroup studies. Together, these three elements enable rational design of either technical or behavioral studies.

8. Research Gaps

Table 8. Research gap matrix

Gap	Evidence from corpus	Priority response	Gap type
Theory under-specification	Only 21/125 core studies explicitly name a coded theory in metadata/abstracts.	Move from descriptive AI effects to mechanism-based models connecting system features, justice/trust, and behavior.	Theoretical
Perception-outcome disconnect	Fairness, trust, and applicant reactions are common, but consequential behavior is less often observed.	Link perceptions to withdrawal, offer acceptance, actual selection, adverse impact, and post-hire outcomes.	Outcome / measurement
Bias evidence needs stronger validation	Bias/discrimination appears in 39 studies and diversity/inclusion in 24.	Combine perceived fairness with subgroup error analysis, adverse-impact metrics, and intersectional audits.	Ethics / method
Human-AI configuration gap	Human-AI collaboration appears in 20 studies, but decision rights and override rules are inconsistently specified.	Manipulate automation level, review authority, override rights, and accountability.	Design / governance

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

Explainability boundary conditions	Explainability/transparency appears in 18 studies; effects are not uniformly positive.	Test explanation type, timing, outcome favorability, task, and AI literacy.	Conceptual
GenAI reproducibility gap	NLP/LLM/GenAI appears in 18 studies and is rapidly expanding.	Report model/version, prompts, stability, data provenance, and applicant- versus employer-side use.	Technology
Stage fragmentation	Studies span attraction, screening, assessment, interview, and final selection.	Track the same applicant across stages and model cumulative trust/fairness/attrition.	Process
Contextual generalization	Evidence is internationally dispersed, but study-site and institutional comparisons remain limited.	Use multi-country and multi-sector designs with measurement invariance and institutional controls.	Contextual
Post-hire validation gap	Quality-of-hire and efficiency are frequent themes, but longer-run validity is less visible.	Link AI selection decisions to onboarding, performance, retention, and career outcomes.	Validity

9. Future Research Agenda

An effective research agenda must do more than merely enumerate overlooked concepts. It needs the identification of inquiries that might help solve existing controversies within the domain and link the inquiries to appropriate research methodologies. Table 9 interprets the corpus-wide gaps with the help of actionable premises.

Table 9. Theory-linked future research agenda

Research domain	**Core question**	**Theoretical anchor**	**Recommended design**
Meaningful human control	When do human review and override rights improve both decision quality and applicant legitimacy?	Sociotechnical Systems; Organisational Justice	Factorial field/online experiments comparing human-only, AI-only, advisory AI, and mandatory-review configurations.
Multi-dimensional fairness	When do statistical fairness and perceived fairness converge or diverge across demographic groups?	Organisational Justice; fairness heuristics	Audit studies + applicant experiments + subgroup error/adverse-impact metrics; intersectional analysis.
Explainability fit	Which explanation types work for which decisions, stages, and applicants?	Justice; Signalling; trust in automation	Manipulate explanation content/timing and outcome favorability; measure comprehension, trust, appeal, and withdrawal.
Applicant journey	How do repeated AI encounters across sourcing, screening, assessment, and interviewing accumulate into trust or attrition?	Signalling; applicant reactions	Longitudinal panel or process-tracing design following candidates across multiple recruitment stages.
GenAI dual-sided use	How do employer-side and applicant-side GenAI jointly change validity, integrity, and fairness?	Strategic interaction; justice	Controlled LLM experiments, prompt/version logging, repeated-run stability tests, and field validation.
Humanized AI interviews	Which social cues improve interaction quality without creating deception, overtrust, or unfair advantage?	Social presence; signaling; justice	Multimodal experiments comparing voice, avatar, intimacy, feedback, and transparency cues across cultures.

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

Accessibility and neurodiversity	How do AI recruitment systems affect candidates with disabilities or neurodivergent interaction patterns?	Inclusion; person-environment fit	Participatory design, multi-group SEM, accessibility audits, and qualitative follow-up with affected groups.
Institutional and cross-cultural context	How do regulation, culture, labour-market institutions, and sector norms shape acceptance and fairness?	Institutional/contextual perspectives	Multi-country samples, measurement invariance, matched sector comparisons, and policy-natural experiments.
Post-hire validity	Do AI-enabled selection gains persist after hire and for whom?	Selection validity; fit	Link recruitment system records to job performance, retention, absenteeism, and career progression over time.

10. Theoretical Contributions

The first contribution of the review is that it recasts the AI recruitment process as a problem of social legitimacy rather than technical deployment. While the models of adoption clarify the rationale behind the introduction of AI in organisations, they do not help understand how applicants react towards the use of AI in recruitment. In this regard, the analysis combines organisational justice and related disciplines with governance and highlights the legitimacy of applicants as a major mechanism of success or failure of AI recruitment.

The paper differentiates between the capabilities and configuration of AI in recruitment. Capability means the ability of AI to perform certain functions, while configuration refers to the way this ability is embedded into processes of employment decisions and information provision. This distinction helps explain some conflicting findings: in one situation, human presence can influence the perceptions of applicants positively; in another one, it can again call into question the objectivity of the process. These contradictions emerge due to different configurations of AI and external conditions.

The review presents a two-dimensional model of responsible AI in recruitment. The process should be evaluated not only in terms of effectiveness but also in terms of legitimacy. Effectiveness refers to the prediction of job performance, costs, and profits, while legitimacy relates to procedural justice, trust, and acceptance of technology. This approach allows comparing various technologies and getting rid of the bias towards the optimisation of one criterion only.

Finally, the paper develops the theory of applicant reaction in the context of AI recruitment. Traditional studies on selection point out that recruitment processes are subject to certain rules ensuring fairness. The introduction of AI complicates the picture by adding new variables connected to its performance, such as level of automation, the degree of transparency, and model behaviour. As a result, the traditional approach is combined with algorithmic hiring approaches.

11. Practical and Governance Implications

Practical implications do not imply that companies should refrain from hiring with the aid of AI. However, deployment should be considered a management decision rather than a purchase of software. It is necessary for companies to define the recruitment task, aim of the model, data input, intended level of automation, decision-making authority, override procedure, explanation policy, and escalation path prior to evaluating its effectiveness. Candidate-facing communication should describe the applicability of AI and emphasise people's roles in this process, especially in termination and final selection situations.

Assessment should be comprehensive. Technical effectiveness indicators, fairness checks, adverse impact studies, accessibility assessment, and the candidate’s experience measures should be additionally used. Companies adopting GenAI and LLMs should also implement prompt and version control. Understanding that any changes in the model may change its screening or recommending behaviour is crucial to assess the model; thus, it is important to document information concerning model version, prompts, search engine results used, and human review.

12. Limitations

There are some limitations of the review, which should be made clear. First of all, the evidence base comes only from Scopus; this means that the important studies that can be found only in Web of Science, PsycINFO, ABI/INFORM, IEEE Xplore, legal databases, or working-paper archives are not represented. Secondly, the

Vol. 12 Issue 6s (October 2026)
ISSN:2208-2190 Pages-123-142
DOI: https://doi.org/10.69980/k10xhx82

query used in Scopus cannot be replicated because it was not kept in the uploaded report. Thirdly, the high-level corpus is built on the titles, abstracts, and keywords.

13. Conclusion

Recent works on the use of artificial intelligence in recruitment and selection have evolved from an initial perspective centred on automation and efficiency to a wider discussion of legitimacy, fairness, trust, inclusion, human control, and candidate experience with emerging results. The 125-study highly confident corpus shows the accelerating development of this situation in comparison with 2023, already reshaped by generative AI and LLM-driven recruitment. Therefore, the focus of the next generation of research should change from the question of whether "AI recruitment" works in general to which AI configurations do work for whom at which stage of recruitment and under which governing conditions.

The integrative framework created in this review positions system design and governance as precursors, justice/trust/control/privacy mechanisms as explanatory processes, and combinations of outcomes of applicants and organisations as joint criteria. In addition, boundary conditions were identified that can explain contrasting results of studies such as the stage of recruitment, outcome favorability, AI literacy of demographic groups, country, and regulation. This construct serves as a basis for further development of theory and empirical designs in this field.

References

1. Acikgoz, Y., Davison, K.H., Compagnone, M., & Laske, M. (2020). Justice Perceptions of Artificial Intelligence in Selection. International Journal of Selection and Assessment, 28(4), 399-416. https://doi.org/10.1111/ijsa.12306
2. Allal-Chérif, O., Yela Aránega, A., & Castaño Sánchez, R. (2021). Intelligent Recruitment: How to Identify, Select, and Retain Talents from around The World Using Artificial Intelligence. Technological Forecasting and Social Change, 169, 120822. https://doi.org/10.1016/j.techfore.2021.120822
3. Bedemariam, R., & Wessel, J.L. (2023). The Roles of Outcome and Race on Applicant Reactions to AI Systems. Computers in Human Behaviour, 148, 107869. https://doi.org/10.1016/j.chb.2023.107869
4. Campion, M.A., & Campion, E.D. (2023). Machine Learning Applications to Personnel Selection: Current Illustrations, Lessons Learned, and Future Research. Personnel Psychology, 76(4), 993-1009. https://doi.org/10.1111/peps.12621
5. Campion, E.D., & Campion, M.A. (2024). Impact of Machine Learning on Personnel Selection. Organizational Dynamics, 53(1), 101035. https://doi.org/10.1016/j.orgdyn.2024.101035
6. Canagasuriam, D., & Lukacik, E.-R. (2025). ChatGPT, Can You Take My Job Interview? Examining Artificial Intelligence Cheating in The Asynchronous Video Interview. International Journal of Selection and Assessment, 33(1), e12491. https://doi.org/10.1111/ijsa.12491
7. Chen, Z. (2023). Collaboration among Recruiters and Artificial Intelligence: Removing Human Prejudices in Employment. Cognition, Technology and Work, 25(1), 135-149. https://doi.org/10.1007/s10111-022-00716-0
8. Clavel, C., d'Armagnac, S., Hebrard, S., Hesters, T., & Potdevin, D. (2025). Humanised AI In Hiring: An Empirical Study of A Virtual AI Job Interviewer's Social Skills on Applicants' Reactions and Experience. International Journal of Human Resource Management, 36(2), 206-234. https://doi.org/10.1080/09585192.2024.2440784
9. Colquitt, J. A. (2001). On The Dimensionality of Organisational Justice: A Construct Validation of a Measure. Journal of Applied Psychology, 86(3), 386-400. https://doi.org/10.1037/0021-9010.86.3.386
10. Dargnies, M.-P., Hakimov, R., & Kübler, D. (2024). Aversion to Hiring Algorithms: Transparency, Gender Profiling, and Self-Confidence. Management Science, 72(1), 285-301. https://doi.org/10.1287/mnsc.2022.02774
11. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease af Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008
12. Deriu, V., Pozharliev, R., & De Angelis, M. (2024). How Trust and Attachment Styles Jointly Shape Job Candidates' AI Receptivity. Journal of Business Research, 179, 114717. https://doi.org/10.1016/j.jbusres.2024.114717
13. Drage, E., & Mackereth, K. (2022). Does AI Debias Recruitment? Race, Gender, and AI's "Eradication of Difference". Philosophy and Technology, 35(4), 89. https://doi.org/10.1007/s13347-022-00543-1
14. Feldkamp, T., Langer, M., Wies, L., & König, C.J. (2024). Justice, Trust, and Moral Judgements When Personnel Selection is Supported By Algorithms. European Journal of Work and Organisational Psychology, 33(2), 130-145. https://doi.org/10.1080/1359432X.2023.2169140

15. Figueroa-Armijos, M., Clark, B.B., & da Motta Veiga, S.P. (2023). Ethical Perceptions Of AI In Hiring And Organisational Trust: The Role of Performance Expectancy and Social Influence. Journal of Business Ethics, 186(1), 179-197. https://doi.org/10.1007/s10551-022-05166-2
16. Fleiß, J., Bäck, E., & Thalmann, S. (2024). Mitigating Algorithm Aversion in Recruiting: A Study on Explainable AI for Conversational Agents. Data Base for Advances in Information Systems, 55(1), 56-87. https://doi.org/10.1145/3645057.3645062
17. Frissen, R., Adebayo, K.J., & Nanda, R. (2023). A Machine Learning Approach to Recognise Bias and Discrimination in Job Advertisements. AI and Society, 38(2), 1025-1038. https://doi.org/10.1007/s00146-022-01574-0
18. Gilliland, S. W. (1993). The Perceived Fairness of Selection Systems: An Organisational Justice Perspective. Academy of Management Review, 18(4), 694-734. https://doi.org/10.5465/amr.1993.9402210155
19. Gonzalez, M.F., Liu, W., Shirase, L., Tomczak, D.L., Lobbe, C.E., Justenhoven, R., & Martin, N.R. (2022). Allying With AI? Reactions Toward Human-Based, AI/Ml-Based, And Augmented Hiring Processes. Computers in Human Behaviour, 130, 107179. https://doi.org/10.1016/j.chb.2022.107179
20. Hofeditz, L., Clausen, S., Rieß, A., Mirbabaie, M., & Stieglitz, S. (2022). Applying XAI To An AI-Based System for Candidate Management to Mitigate Bias and Discrimination in Hiring. Electronic Markets, 32(4), 2207-2233. https://doi.org/10.1007/s12525-022-00600-9
21. Hu, J., Huang, G.I., Wong, I.A., & Wan, L.C. (2024). AI Trust Divide: How Recruiter-Candidate Roles Shape Tourism Personnel Decision-Making. Annals of Tourism Research, 109, 103860. https://doi.org/10.1016/j.annals.2024.103860
22. Kelan, E.K. (2024). Algorithmic Inclusion: Shaping the Predictive Algorithms of Artificial Intelligence jn Hiring. Human Resource Management Journal, 34(3), 694-707. https://doi.org/10.1111/1748-8583.12511
23. Kim, S.C., Hernandez, I., & Li, J. (2026). When Algorithms Favour the Underrepresented – Race and Gender Biases in LLM Résumé Evaluations. Journal of Personnel Psychology, 25(3), 148-157. https://doi.org/10.1027/1866-5888/a000388
24. Kwok, L., Chuang, N.-K., & Huang, Y.-K. (2026). Staying Ahead: A Critical Assessment of the GenAI-Assisted Hiring Process Using the OECD AI Principles. Journal of Hospitality and Tourism Research, 50(6), 886-903. https://doi.org/10.1177/10963480251391278
25. Landers, R.N., Auer, E.M., Dunk, L., Langer, M., & Tran, K.N. (2023). A Simulation of the Impacts of Machine Learning to Combine Psychometric Employee Selection System Predictors on Performance Prediction, Adverse Impact, and Number of Dropped Predictors. Personnel Psychology, 76(4), 1037-1060. https://doi.org/10.1111/peps.12587
26. Langer, M., König, C.J., Back, C., & Hemsing, V. (2023). Trust in Artificial Intelligence: Comparing Trust Processes Between Human and Automated Trustees in Light of Unfair Bias. Journal of Business and Psychology, 38(3), 493-508. https://doi.org/10.1007/s10869-022-09829-9
27. Langer, M., König, C.J., & Busch, V. (2021). Changing The Means of Managerial Work: Effects of Automated Decision Support Systems on Personnel Selection Tasks. Journal of Business and Psychology, 36(5), 751-769. https://doi.org/10.1007/s10869-020-09711-6
28. Lee, J. D., & See, K. A. (2004). Trust In Automation: Designing for Appropriate Reliance. Human Factors, 46(1), 50-80. https://doi.org/10.1518/hfes.46.1.50_30392
29. Liu, X., & Su, C. (2026). Fine-Tuning Large Language Models for Automated Resume Screening in Human Resource Management: A Comparative Performance Analysis. Journal of Engineering, Project, and Production Management, 16(5). https://doi.org/10.32738/JEPPM-2026-0092
30. Noble, S.M., Foster, L.L., & Craig, S.B. (2021). The Procedural and Interpersonal Justice of Automated Application and Resume Screening. International Journal of Selection and Assessment, 29(2), 139-153. https://doi.org/10.1111/ijsa.12320
31. Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The Adoption of Artificial Intelligence in Employee Recruitment: The Influence of Contextual Factors. International Journal of Human Resource Management, 33(6), 1125-1147. https://doi.org/10.1080/09585192.2021.1879206
32. Park, J., & Jung, Y. (2025). Exploring Cultural Differences in AI-Based Interviews: Innovativeness and Justice Perceptions among Job Applicants in the United States and South Korea. Human Resource Management, 64(4), 1161-1178. https://doi.org/10.1002/hrm.22303
33. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hrobjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., Stewart, L. A., Thomas,

J., Tricco, A. C., Welch, V. A., Whiting, P., & Moher, D. (2021). The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

34. Pessach, D., Singer, G., Avrahami, D., Chalutz Ben-Gal, H., Shmueli, E., & Ben-Gal, I. (2020). Employee Recruitment: A Prescriptive Analytics Approach Via Machine Learning and Mathematical Programming. Decision Support Systems, 134, 113290. https://doi.org/10.1016/j.dss.2020.113290
35. Pillai, R., & Sivathanu, B. (2020). Adoption of Artificial Intelligence (AI) for Talent Acquisition In IT/Ites Organizations. Benchmarking, 27(9), 2599-2629. https://doi.org/10.1108/BIJ-04-2020-0186
36. Rigotti, C., & Fosch-Villaronga, E. (2024). Fairness, AI & Recruitment. Computer Law and Security Review, 53, 105966. https://doi.org/10.1016/j.clsr.2024.105966
37. Robertson Nogues, A. (2026). Automating Injustice: A Critical Analysis of AI-Assisted Recruitment Processes from A Disability Justice Perspective. AI and Society, 41(4), 2761-2768. https://doi.org/10.1007/s00146-025-02581-7
38. Sivakaminathan, S.S., & Musi, E. (2026). ChatGPT is a Gender Bias Echo Chamber in HR Recruitment: An NLP Analysis and Framework to Uncover The Language Roots of Bias. AI and Society, 41(4), 2841-2861. https://doi.org/10.1007/s00146-025-02564-8
39. Snyder, H. (2019). Literature Review as a Research Methodology: An Overview and Guidelines. Journal of Business Research, 104, 333-339. https://doi.org/10.1016/j.jbusres.2019.07.039
40. Spence, M. (1973). Job Market Signalling. The Quarterly Journal of Economics, 87(3), 355-374. https://doi.org/10.2307/1882010
41. Suen, H.-Y., & Hung, K.-E. (2024). Revealing the Influence of AI and Its Interfaces on Job Candidates' Honest and Deceptive Impression Management in Asynchronous Video Interviews. Technological Forecasting and Social Change, 198, 123011. https://doi.org/10.1016/j.techfore.2023.123011
42. Thompson, I., Koenig, N., Mracek, D.L., & Tonidandel, S. (2023). Deep Learning in Employee Selection: Evaluation of Algorithms to Automate the Scoring of Open-Ended Assessments. Journal of Business and Psychology, 38(3), 509-527. https://doi.org/10.1007/s10869-023-09874-y
43. Tian, X., Pavur, R., Han, H., & Zhang, L. (2023). A Machine Learning-Based Human Resources Recruitment System for Business Process Management: Using LSA, BERT and SVM. Business Process Management Journal, 29(1), 202-222. https://doi.org/10.1108/BPMJ-08-2022-0389
44. Tippavajjula, A.S.L., Shankar, A., & Majumdar, B. (2026). Beyond Technological Affordances: Trust and Continued Intention to Use AI-Enabled Recruitment Systems across Neurodivergent and Neurotypical Applicants. Acta Psychologica, 268, 107352. https://doi.org/10.1016/j.actpsy.2026.107352
45. Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. British Journal of Management, 14(3), 207-222. https://doi.org/10.1111/1467-8551.00375
46. Tursunbayeva, A., Fernandez, V., Gallardo-Gallardo, E., & Moschera, L. (2026). Artificial Intelligence and Digital Data in Recruitment. Exploring Business and Engineering Candidates' Perceptions Of Organizational Attractiveness. European Management Journal, 44(2), 235-244. https://doi.org/10.1016/j.emj.2025.03.002
47. van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the Machine Meets The Expert: An Ethnography Of Developing AI For Hiring. MIS Quarterly: Management Information Systems, 45(3), 1557-1580. https://doi.org/10.25300/MISQ/2021/16559
48. van Esch, P., Black, J.S., & Ferolie, J. (2019). Marketing AI Recruitment: The Next Phase in Job Application and Selection. Computers in Human Behaviour, 90, 215-222. https://doi.org/10.1016/j.chb.2018.09.009
49. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425-478. https://doi.org/10.2307/30036540
50. Wesche, J.S., & Sonderegger, A. (2021). Repelled at First Sight? Expectations and Intentions of Job-Seekers Reading about AI Selection in Job Advertisements. Computers in Human Behaviour, 125, 106931. https://doi.org/10.1016/j.chb.2021.106931
51. Zhang, L., & Yencha, C. (2022). Examining Perceptions towards Hiring Algorithms. Technology In Society, 68, 101848. https://doi.org/10.1016/j.techsoc.2021.101848