ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

The Legitimation-Validation Paradox in AI-Driven Talent Acquisition: A Critical Systematic Review

Hajar MOUNTASSIR, (***PhD candidate)***
Faculty of Law, Economics, and Social Sciences - Souissi,
Mohamed V University of Rabat, Morocco.

Hicham BENYASSINE, ***(Full Professor)***
Faculty of Law, Economics, and Social Sciences - Souissi,
Mohamed V University of Rabat, Morocco.

Correspondence address :	LARCEPEM / Département d'économie et de gestion. Faculté des sciences juridiques, économiques et sociales, Souissi-Rabat. Université Mohammed V de Rabat.
Disclosure Statement :	The authors declare that they have not received any financial support that could have influenced the objectivity of this study. They take full responsibility for any potential plagiarism, the use of artificial intelligence in the writing process, as well as for the results presented in this article.
Conflict of Interest :	The authors report no conflicts of interest.
Cite this article :	MOUNTASSIR, H., & BENYASSINE, H. (2026). The Legitimation-Validation Paradox in AI-Driven Talent Acquisition: A Critical Systematic Review. *International Journal of Accounting, Finance, Auditing, Management and Economics*, *6*(7), 1–33. https://doi.org/10.5281/zenodo.20592770
License	**This is an open access article under the CC BY-NC-ND license**

Received: 27/04/2026 *Accepted: 09/06/2026*

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

The Legitimation-Validation Paradox in AI-Driven Talent Acquisition: A Critical Systematic Review

Résumé :

Les outils de recrutement fondés sur l'IA sont de plus en plus mobilisés pour trier, apparier, évaluer et sélectionner les candidats, alors que les preuves relatives à leur validité prédictive demeurent moins établies que leur légitimité organisationnelle et leur visibilité académique. Cet article examine cette tension comme un paradoxe de légitimation-validation, c'est-à-dire une situation dans laquelle des technologies deviennent institutionnellement acceptées alors que leurs revendications centrales de performance restent insuffisamment étayées. L'étude propose une revue systématique critique à visée théorique, fondée sur le protocole PRISMA 2020 et sur une cartographie des controverses plutôt que sur une synthèse thématique conventionnelle. Le corpus comprend 110 publications, incluant des études identifiées dans la fenêtre de recherche 2015–2024 et des travaux fondateurs repérés par la recherche rétrospective des citations. Les recherches ont été conduites dans Scopus, Web of Science, EBSCO Business Source, PsycINFO, IEEE Xplore, JSTOR, Google Scholar, ProQuest Dissertations et Cairn.info. La littérature grise et les publications professionnelles ont été exclues de la base probatoire issue des recherches en bases, sauf lorsqu'elles servaient de sources contextuelles ou fondatrices repérées par le suivi des citations. L'analyse met en évidence une asymétrie persistante entre des revendications d'efficacité relativement bien documentées et des preuves plus faibles, contestées ou insuffisamment répliquées concernant la validité critérielle, l'équité et la performance prédictive. En distinguant efficacité opérationnelle, validité prédictive et équité, l'article réoriente le débat vers la question préalable de la validation indépendante. Les résultats doivent être interprétés avec prudence, compte tenu de la composition majoritairement occidentale et anglophone du corpus.

Mots clés : Intelligence artificielle ; Acquisition de talents ; Paradoxe légitimation-validation ; Isomorphisme institutionnel ; Recrutement algorithmique ; Revue systématique.
JEL Classification : M51; O33; M15; D02; J71; L15.
Type du papier : Recherche Théorique

Abstract :

AI-based recruitment tools are increasingly used to screen, match, assess, and select candidates, yet the evidence supporting their predictive validity remains less developed than their organizational legitimacy and scholarly visibility. This article examines this tension as a legitimation-validation paradox, defined as a condition in which technologies become institutionally accepted while their core performance claims remain insufficiently substantiated. The study conducts a critical systematic review with a theoretical aim, following the PRISMA 2020 protocol and applying controversy mapping rather than conventional thematic synthesis. The corpus comprises 110 publications, including studies identified within the 2015–2024 search window and foundational works retrieved through backward citation searching. Searches were conducted in Scopus, Web of Science, EBSCO Business Source, PsycINFO, IEEE Xplore, JSTOR, Google Scholar, ProQuest Dissertations, and Cairn.info. Grey literature and trade publications were excluded from the database-search evidence base, except when used as contextual or foundational sources identified through citation tracking. The analysis reveals a persistent asymmetry between relatively well-documented efficiency claims and weaker, contested, or insufficiently replicated evidence concerning criterion validity, fairness, and predictive performance. By distinguishing operational efficiency from predictive validity and fairness, the article reorients the AI recruitment debate toward the prior question of independent validation. The findings should be interpreted cautiously, given the predominantly Western and Anglophone composition of the reviewed corpus.

Keywords: Artificial Intelligence; Talent Acquisition; Legitimation–Validation Paradox; Institutional Isomorphism; Algorithmic Recruitment; Systematic Review.
Classification JEL: M51; O33; M15; D02; J71; L15.
Paper type: Theoretical Research

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

1. Introduction

The use of artificial intelligence (AI) in talent acquisition has moved expeditiously from pilot experimentation to mainstream organizational practice, yielding a parallel expansion of academic research on its ethical, organizational, and practical implications. Organizations across sectors now leverage AI tools to screen, assess, and select job candidates at unprecedented scale, while a substantial body of scholarship has emerged to analyze the ethical implications, organizational consequences, and practitioner experiences associated with this deployment. In this review, AI recruitment tools refer to algorithmic systems used across the recruitment funnel, including résumé-screening tools, candidate-matching systems, recruitment chatbots, and algorithmic video-interview platforms, whose validity expectations differ according to whether they automate administrative filtering, infer candidate-job fit, manage candidate interaction, or generate evaluative predictions. Yet a question that should logically precede all others has received surprisingly limited sustained attention: do these tools actually work? The accumulated evidence, as this review shows, does not support an affirmative answer. No robust body of independently replicated criterion-validity evidence was identified in the reviewed corpus to demonstrate that AI recruitment technologies predict subsequent job performance more accurately than the methods they replace. By contrast, efficiency-related claims, particularly regarding reduced screening time and recruitment costs, are more consistently documented. This asymmetry between institutional adoption and empirical substantiation constitutes the legitimation-validation paradox examined in this review. It is this paradox, rather than the more familiar cataloguing of technological capabilities, organizational dynamics, and ethical concerns, that motivates the present article.

The observation that AI recruitment tools lack independent validation evidence is not new. Tambe et al. (2019) identified data-quality limitations and weaknesses in causal reasoning as fundamental barriers to effective AI use in human resource management. Ployhart et al. (2017) emphasized that new selection technologies have historically been adopted before adequate psychometric validation. Raghavan et al. (2020) found that commercial hiring-algorithm vendors rarely disclose validation data or fairness-testing protocols. The contribution of the present analysis lies in arguing that this validation deficit is not merely a gap awaiting correction through additional research, but a structurally sustained condition maintained by identifiable institutional mechanisms (Bellamy et al., 2019). The question therefore shifts from when validation evidence will catch up with adoption to which institutional forces sustain adoption in the persistent absence of validation evidence, and why the academic community has not treated this absence as the central problematic of the field.

Prior systematic reviews have synthesized the AI recruitment literature without foregrounding this paradox. Köchling and Wehner (2020) mapped algorithmic discrimination and fairness concerns across 60 studies, producing a valuable ethical taxonomy that nevertheless accepted the existence and functional relevance of AI recruitment tools rather than scrutinizing the evidentiary basis of that assumption. Hunkenschroer and Luetge (2022) reviewed the ethics of AI-enabled recruitment across 56 studies, developing a research agenda grounded in applied ethics, but similarly treating these technologies as objects warranting normative analysis rather than questioning whether their foundational claims justify such attention. Meijerink and Bondarouk (2023) provided a broader review of HRM technology effects on employees across 75 articles, without focusing specifically on talent acquisition or addressing the validation deficit. Each of these reviews advanced knowledge within a specific analytical frame, but none interrogated the relationship between the institutional legitimacy these tools have acquired and the scientific evidence, or lack thereof, supporting their deployment. The cumulative effect of scholarly engagement with AI recruitment tools, including ethical critique, organizational analysis, and practitioner-perception studies, has been to confer

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND
IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

epistemic respectability on technologies whose criterion validity remains undemonstrated. This is not a criticism of individual scholars, but an observation about the structural consequences of how a research field organizes itself around a phenomenon.

The theoretical perspective adopted in this review draws on institutional theory, particularly the mechanisms of isomorphic change identified by DiMaggio and Powell (1983) and the broader framework of organizational legitimation developed by Suchman (1995). Institutional theory provides the conceptual resources to explain how practices gain acceptance and persistence not through demonstrated technical superiority, but through conformity to normative expectations, imitation of perceived leaders, and adaptation to regulatory pressures. Applied to AI recruitment, this perspective reframes the adoption phenomenon: organizations deploy these tools not because evidence demonstrates that they improve selection quality, but because peer organizations are deploying them, because regulatory environments permit their use without requiring validation, because professional norms increasingly associate AI adoption with managerial competence, and because vendor marketing has successfully substituted promotional rhetoric for scientific evidence. These questions are intentionally organized as a multi-level architecture, moving from evidentiary assessment, to institutional explanation, and finally to reflexive analysis of the scholarly field:

RQ1: *What is the current state of independent criterion-validity evidence for AI recruitment technologies, and how does this evidence compare with the validation standards historically applied to personnel-selection instruments?*

RQ2: *Through which institutional mechanisms have AI recruitment tools acquired organizational legitimacy despite the absence of independent validation evidence?*

RQ3: *In what ways does the structure of academic literature on AI in talent acquisition participate in, or challenge, the legitimation of unvalidated technologies?*

These questions deviate from the standard framing of AI recruitment reviews, which often analyse existing tools, adoption processes, ethical issues, and research gaps. The present review contributes theoretically by conceptualizing the legitimation-validation paradox, methodologically by using controversy mapping, and practically by re-prioritizing independent criterion-validity evidence as a prerequisite for responsible AI recruitment.

2. Literature Review

The theoretical foundations of AI-driven talent acquisition are built from a composite conceptual architecture. Several intellectual traditions have developed in parallel without always converging into a unified analytical framework. The result is a rich but fragmented conceptual field. Beneath this plurality, however, lies a fundamental tension that remains insufficiently theorized and that this review places at the center of its analysis. AI recruitment tools are subject to two analytically distinct and frequently contradictory requirements. First, they require institutional legitimacy, defined by Suchman (1995) as the generalized perception that an action is desirable, proper, and appropriate within a socially constructed system of norms, values, beliefs, and definitions. This legitimacy requires conformity to organizational norms, regulatory expectations, and professional understandings of what constitutes acceptable hiring practice. Second, they must demonstrate empirical validity, namely robust and reproducible evidence that their outputs predict job performance and do not systematically discriminate against protected groups (American Educational Research Association, American Psychological Association & National Council on Measurement in Education, 2014). In this review, the central deficit concerns criterion validity, understood as evidence that algorithmic outputs predict subsequent job performance. Other validity dimensions remain relevant but analytically secondary: construct validity concerns whether the tool measures the intended attribute, fairness validity concerns non-discriminatory

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND
IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

performance across groups, transportability concerns stability across organizational settings, and external validity concerns generalizability beyond the original validation context. These two imperatives do not necessarily coincide. A critical reading of the literature suggests that they often diverge. Tools may become widely adopted and acquire de facto legitimacy while lacking robust psychometric or predictive validity (Raghavan et al., 2020). Conversely, technically superior approaches may fail to diffuse because they disrupt institutionalized hiring scripts or threaten the professional authority of human gatekeepers (DiMaggio & Powell, 1983). The paradox therefore does not lie in individual tools taken in isolation, but in this broader structural contradiction. Accordingly, conceptual works are used to define the paradox, empirical studies to assess evidentiary support, legal and normative texts to clarify regulatory constraints, and management publications to understand professional and organizational legitimation. Its analysis requires seven research domains, used at different levels: e-HRM, AI-HRM, talent acquisition, bias, justice, trust, and automation-augmentation provide contextual foundations, while institutional theory constitutes the main explanatory framework.

The first intellectual legacy is e-HRM. AI in recruitment is embedded in an earlier trajectory of HR digitalization. Strohmeier (2007) offered one of the earliest systematic analyses of electronic HRM by distinguishing operational, relational, and transformational applications, a distinction that continues to inform contemporary analysis. Bondarouk et al. (2017) extended this line of inquiry through a four-decade review, showing a clear shift from administrative automation toward strategic workforce analytics. The central point is that this trajectory cannot be reduced to a purely technical dynamic. Orlikowski's (1992) concept of the duality of technology, grounded in structuration theory, argues that technologies are simultaneously shaped by and constitutive of the organizational structures in which they are embedded. Applied to AI in recruitment, this perspective shows that algorithmic tools do not merely automate existing processes; they recursively reconfigure the rules, resources, and power relations that govern talent acquisition. Townley's (1993) Foucauldian analysis introduces an additional analytical dimension: by rendering candidates calculable through psychometric scoring, competency profiling, and now algorithmic ranking, HR technologies participate in the production of specific "truths" about candidate value, truths that are simultaneously epistemic and political. Mainstream AI-HRM literature tends to under-theorize this dimension, although it becomes especially important when algorithmic opacity may amplify existing power asymmetries (Mittelstadt et al., 2016).

Within this trajectory, the shift from e-HRM to AI-based HRM requires specific attention. This shift is not simply an intensification of earlier digitalization. Earlier electronic systems digitized existing processes without substantially transforming the architecture of decision-making. AI tools, by contrast, generate autonomous recommendations, learn from historical data patterns, and operate with degrees of opacity that challenge traditional accountability structures (Tambe et al., 2019). Stone et al. (2015) anticipated this transformation by arguing that algorithmic decision-making would redraw the boundary between human and machine judgment in recruitment. Weick's (1995) sensemaking perspective provides a complementary analytical lens for examining how HR practitioners retrospectively rationalize and narratively construct their interactions with AI, often producing plausible rather than accurate accounts of algorithmic behavior. This remains a critical but insufficiently examined dimension, with major implications for how validation evidence is interpreted and operationalized.

The analysis can then be narrowed to talent acquisition itself. Around 2018, academic attention intensified significantly, stimulated by commercial tools such as intelligent applicant-tracking systems, résumé parsers, chatbots, and asynchronous video interviews with affect recognition (Black & van Esch, 2020). Hmoud and Laszlo (2019) asked whether AI would eventually replace humans in recruitment and concluded that augmentation, rather than

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

replacement, was the more likely trajectory. This augmentation thesis has since become dominant, supported by Jarrahi's (2018) model of human-AI symbiosis and Autor's (2015) economic analysis showing that automation historically reconfigures occupational roles rather than eliminating them. This reading must nevertheless be complemented by labor-economics perspectives. Spence's (1973) signaling theory reminds us that recruitment markets are characterized by informational asymmetry: employers cannot directly observe candidate quality and therefore rely on proxies such as credentials, experience, or algorithmic scores. AI does not resolve this asymmetry; it relocates and algorithmically mediates it by replacing one set of imperfect proxies, human judgment, with another, statistical inference from historical data. Crucially, the validity of these new proxies cannot be assumed, yet many commercial tools have not provided the necessary evidence (Raghavan et al., 2020). Upadhyay and Khandelwal (2018) offered a practitioner-oriented mapping of AI applications in recruitment, including screening, matching, and engagement. More recently, Paramita et al. (2024) identified six organizational dimensions shaping AI adoption. Duggan et al. (2020) further showed that algorithmic management extends beyond corporate HR into gig-economy platforms, thereby widening the scope of legitimate inquiry.

A related concern, and probably the most extensively examined one, concerns algorithmic bias. The Amazon case documented by Dastin (2018) constituted a turning point: an internal recruitment tool was found to penalize résumés mentioning women's colleges. Scholarly responses have been both technical and normative. Raghavan et al. (2020) identified substantial gaps between vendor promises and actual bias-mitigation practices. Mehrabi et al. (2021) provided a major survey of bias and fairness in machine learning, while Buolamwini and Gebru (2018) demonstrated intersectional accuracy gaps in commercial gender-classification systems, findings directly relevant to video-interview technologies. Köchling and Wehner (2020) systematically catalogued how bias enters training data, model specification, and deployment. Yet bias is not merely a technical problem. Mittelstadt et al. (2016) identified six normative concerns: inconclusive, inscrutable, and misguided evidence, together with unfair outcomes, transformative effects, and traceability problems. In recruitment, these concerns are intensified by the high-stakes and asymmetric nature of employment: candidates bear the personal costs of errors while having limited recourse against opaque systems. This explains why the European Union AI Act classifies employment-related AI as high-risk, requiring conformity assessment, transparency, and human oversight (European Parliament, 2024). Veale and Borgesius (2021) offer a precise legal analysis, highlighting both the potential and the interpretive loopholes of this regulatory approach. Wachter et al. (2018) propose counterfactual explanations as a practical way to support explainability without disclosing trade secrets, a contribution directly relevant to HR technology vendors.

Organizational justice constitutes another central dimension of the debate. Gilliland's (1993) model of procedural justice in selection has proven remarkably durable. Newman et al. (2020) extended this model to algorithmic contexts through the concept of algorithmic reductionism, defined as the compression of multidimensional human attributes into computable variables, generating justice concerns that older frameworks do not fully capture. Acikgoz et al. (2020) found that transparency and explainability are critical moderators of candidate acceptance. Langer et al. (2019) experimentally showed that resistance to algorithmic evaluation increases sharply when stakes are high. These findings converge with Kellogg et al.'s (2020) broader work on how algorithmic authority is contested within organizations.

This issue leads directly to the question of trust in AI. Glikson and Woolley's (2020) influential review distinguishes cognitive trust, based on perceived reliability, from affective trust, based on emotional connection. AI mainly generates cognitive trust, while affective trust remains far more difficult to establish. Dietvorst et al. (2015) conceptualized algorithm

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND
IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

aversion, showing that individuals disproportionately abandon algorithms after observing a single error, even when the algorithm performs better than humans on average. Logg et al. (2019), however, identified algorithm appreciation, showing that individuals sometimes prefer algorithmic judgment. This apparent contradiction is best explained by contextual dependence. Such contextual dependence is particularly strong in recruitment, where consequences are high and opacity may intensify uncertainty. The explainable-AI literature directly addresses this trust deficit by distinguishing intrinsic interpretability from post hoc explainability (Arrieta et al., 2020). The extent to which recruitment AI can provide meaningful explanations to candidates, HR professionals, or regulators directly conditions the legitimacy claims that vendors can credibly make. Trust, explainability, and legitimacy therefore converge at the micro level within the same paradox that this review identifies at the macro level.

Another central dimension concerns the automation-augmentation paradox. Raisch and Krakowski (2021) provide an integrative lens for understanding this tension. Organizations face a fundamental trade-off between using AI for automation, which may generate efficiency gains but risks deskilling, and using AI for augmentation, which preserves human agency but increases coordination complexity. In recruitment, this tension is particularly acute because the boundary between automatable tasks, such as résumé screening, and augmentation-intensive tasks, such as assessing cultural fit, remains both contested and shifting (Charlwood & Guenole, 2022). Lebovitz et al. (2021) introduce a further recursive difficulty: the "ground truth" on which AI training depends is itself a socially constructed artifact of expert judgment, which complicates any simplistic claim of algorithmic superiority.

Finally, the institutional dimension remains the least developed but possibly one of the most consequential. Neo-institutional theory provides the tools for explaining cross-contextual variation (DiMaggio & Powell, 1983; Scott, 2014). Brewster (1999) showed that national frameworks, collective bargaining arrangements, and cultural orientations produce divergent HR configurations rather than convergence toward a single model. Pan et al. (2022) applied this argument directly to AI recruitment adoption and found that regulatory environments, sectoral norms, and organizational culture moderate adoption trajectories. The central implication is that legitimation is institutionally situated. In jurisdictions characterized by strong data protection, union oversight, and worker consultation, such as European works councils, the legitimation demands imposed on AI vendors differ qualitatively from those prevailing in lighter-touch regulatory contexts. Suchman's (1995) three types of legitimacy, pragmatic, moral, and cognitive, help structure this interpretation. Pragmatic legitimacy may travel across borders, but moral and cognitive legitimacy remain deeply embedded in institutional contexts. This observation is directly connected to the paradox examined in this review: validation evidence alone cannot guarantee legitimacy everywhere because legitimation is a social process, not a purely epistemic one (Suddaby et al., 2017). Conversely, institutional approval cannot substitute for validation, since compliance does not prove that a tool actually selects better candidates.

As summarized in Table 1, the reviewed traditions provide complementary insights, but only institutional theory directly explains how legitimacy can emerge and persist without equivalent evidentiary validation. More fundamentally, the field has not systematically theorized this relationship as one between competing logics. Feldman and Pentland's (2003) distinction between performative routines, that is, routines enacted in practice, and ostensive routines, that is, abstract ideals, is useful in this respect. When these two dimensions diverge, as the evidence suggests they often do, HR professionals may implement practices that they cannot empirically validate within environments that reward conformity rather than evidentiary fidelity. This structural tension constitutes the core of the paradox examined in this review. The reviewed traditions converge on a common tension: AI recruitment tools are

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

organizationally legitimized before their predictive validity is fully established. The contextual traditions explain why these tools matter for HRM, fairness, trust, and automation; institutional theory is privileged because it directly explains how legitimacy can emerge and persist without equivalent evidentiary validation. The following methodological section specifies the protocol used to investigate it.

Table 1: Analytical positioning of the main theoretical traditions

Tradition	Analytical role	Main limitation	Link with the paradox
e-HRM and AI-HRM	Contextualizes the digital transformation of HR practices	Does not explain why weakly validated tools become legitimate	Shows the technological trajectory behind AI recruitment
Talent acquisition and selection	Specifies the recruitment domain and the validity problem	Often assumes that AI tools improve selection quality	Locates the criterion-validity deficit
Bias, fairness, and regulation	Identifies ethical and legal risks of algorithmic hiring	Focuses more on governance than on predictive validity	Shows why unvalidated tools still require scrutiny
Justice, trust, and explainability	Explains candidate and practitioner acceptance	Explains perceptions more than institutional diffusion	Shows how legitimacy can emerge despite uncertainty
Automation-augmentation	Clarifies the changing boundary between human and machine judgment	Does not fully explain adoption without validation	Shows why AI tools become organizationally attractive
Institutional theory	Provides the main explanatory framework	Requires empirical testing in future research	Explains how legitimacy can persist without robust validation

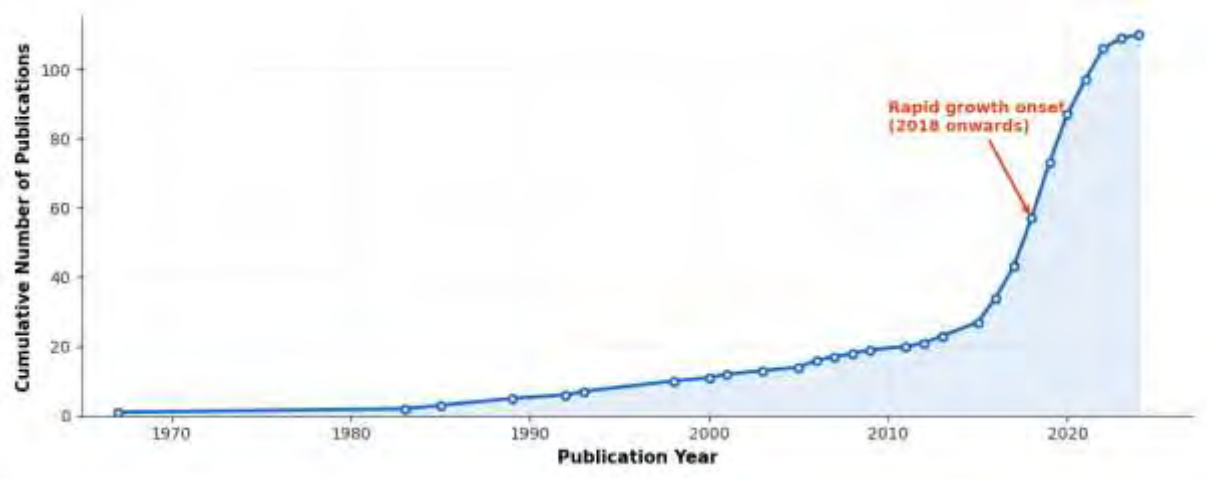
Source: Authors

3. Methodological Protocol

This review follows the PRISMA 2020 guidelines, with one significant adaptation: the synthesis method replaces conventional thematic synthesis with controversy mapping (Page et al., 2021). Controversy mapping, derived from science and technology studies, treats scholarly disagreements, evidentiary asymmetries, and unstated assumptions as primary objects of analysis rather than as obstacles to smooth synthesis (Venturini, 2010). This approach is particularly suited to a field in which the central phenomenon, the legitimacy of unvalidated technologies, is itself a controversy that conventional thematic synthesis would flatten rather than expose.

3.1. Search Strategy

Figure 1: Cumulative distribution of reviewed publications by year.



Note: Pre-2015 publications correspond to foundational theoretical, methodological, or psychometric sources identified through backward citation searching; they are not part of the main 2015–2024 database-search window. ***Source: Authors***

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

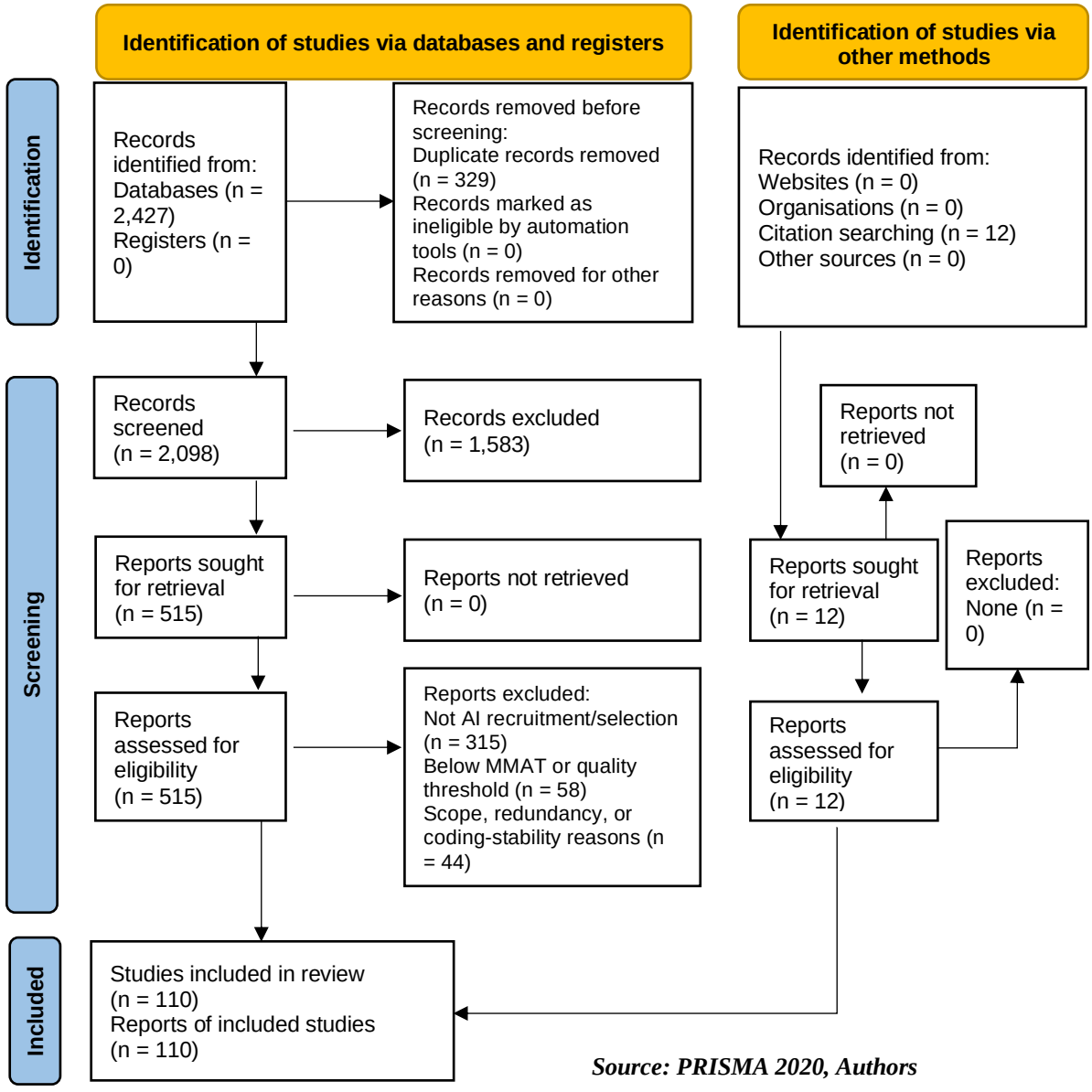
The search strategy encompassed 9 databases, between January and March 2025. The complete database-specific search strings, field restrictions, search period, records retrieved, and deduplication protocol are provided in Appendix A. The temporal window covered the period from 2015 to 2024. Foundational works published before 2015 were initially identified through backward citation searching. The cumulative distribution of reviewed publications is reported in Figure 1, with a marked acceleration after 2018.

Forward citation tracking from the ten most-cited articles identified twelve additional contributions. This concentration entails methodological implications for the field, as it suggests that theoretical consolidation has not yet occurred and that current conceptual frameworks remain provisional and contested.

3.2. Eligibility Criteria and Quality Appraisal

Studies were deemed eligible for inclusion if they met the following criteria: peer-reviewed publications written in English or French and addressed AI technologies in recruitment or personnel selection. The exclusion criteria removed grey literature, trade publications, and studies in which AI appeared only as a peripheral issue.

Figure 2: PRISMA 2020 flow diagram.



Source: PRISMA 2020, Authors

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND
IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

MMAT was applied only to empirical and mixed-methods studies, while conceptual, legal, and review articles were assessed for theoretical relevance, analytical centrality, and contribution to controversy mapping. Empirical studies scoring below three out of five applicable MMAT criteria were excluded (Hong et al., 2018). Inter-coder reliability was assessed using Cohen's kappa at both the title-and-abstract screening and full-text stages. Cohen's kappa reached $\kappa = 0.84$ for title-and-abstract screening and $\kappa = 0.89$ for full-text screening, indicating almost perfect agreement (Landis & Koch, 1977). The selection pathway is documented in Figure 2. The final corpus of included studies is provided in Appendix B, and the MMAT application rule is reported in Appendix C.

3.3. Controversy-Mapping Synthesis

Rather than synthesizing findings into harmonized thematic categories, the synthesis protocol identified eight empirical claims recurrently addressed across the corpus and mapped each claim along 2 axes: consensus status, classified as convergent, contested, weakly supported, or emerging, and evidentiary weight, assessed through convergence across independent studies, methodological rigor, and sample diversity. This approach was designed to make disagreements, evidentiary asymmetries, and unstated assumptions visible rather than resolving them into artificial coherence. The resulting controversy matrix (Figure 4) constitutes a central analytical instrument that disciplines the interpretive claims advanced in Section 4. The eight claims were defined through an abductive coding process combining recurrent claims observed in the corpus with the article's theoretical focus on validation and legitimation. Evidence levels were assigned according to independent convergence, methodological rigor, and contextual diversity; coding disagreements were resolved through discussion and recoding until consensus. The codebook included 14 extraction variables applied to each study. Analytical coding stability was assessed by monitoring whether the final twenty coded studies modified the claim categories or evidence-level rules; after the ninety-first study, no category or classification rule changed.

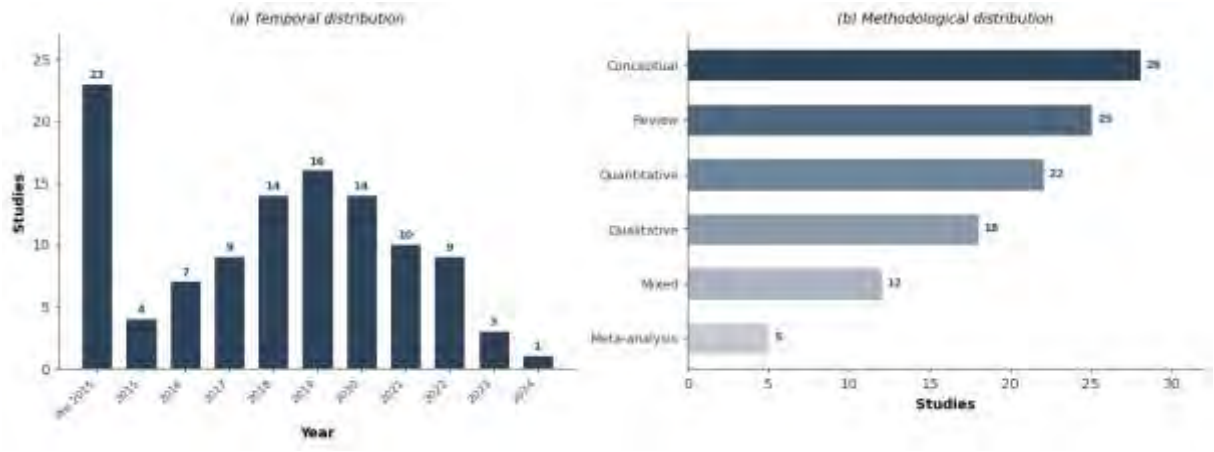
The initial search identified 2,427 records. After duplicate removal (n = 329), title-and-abstract screening excluded 1,583 records, leaving 515 records for full-text assessment. Full-text assessment excluded 315 records, and MMAT/source-appropriate quality appraisal excluded 58 studies, leaving 142 above-threshold records. A further 44 records were removed for scope, redundancy, or coding-stability reasons, leaving 98 database-search studies; 12 supplementary citation-tracking studies were then added, producing the final corpus of 110 publications. The descriptive characteristics of this corpus are examined in the following section, with particular attention to how the composition of the evidence base conditions the interpretive claims that the field can legitimately support. To improve transparency, the search protocol and deduplication procedure are provided in Appendix A, the final corpus in Appendix B, the coding grid and MMAT rule in Appendix C, and the consensus and evidence-level rules in Appendix D.

4. Descriptive Profile of the Corpus

The bibliometric characteristics of the corpus are not merely descriptive. They constitute evidence about the structural conditions under which knowledge on AI-driven talent acquisition has been produced, and they carry direct implications for the legitimation-validation paradox examined in the subsequent analysis.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

Figure 3: Temporal and methodological distribution.



Source: Authors

The temporal profile (Figure 3) shows that 63 of the 110 publications, representing 57.3% of the corpus, were published between 2018 and 2022, while 23 pre-2015 foundational sources were retained through backward citation searching for theoretical, methodological, or psychometric grounding. This period was catalyzed by two major events: the public disclosure that Amazon had discontinued an AI recruitment tool after discovering systematic gender bias, and the intensification of regulatory debate surrounding the European Union General Data Protection Regulation (Dastin, 2018). The rapid growth of scholarly attention during this period is analytically significant. A field that expands this quickly is one in which the pressure to publish on a topical phenomenon may outpace the accumulation of robust evidence, creating conditions in which conceptual commentary and normative analysis occupy the space that empirical investigation has not yet filled. The methodological profile (Figure 3) confirms this pattern. Conceptual and theoretical contributions constitute the largest category, with 28 studies, or 25.5% of the total, followed by review and synthesis articles, with 25 studies, or 22.7%. Quantitative empirical studies account for 22 contributions, or 20.0%, whilst qualitative empirical research comprises 18 studies, or 16.4%. Studies using mixed methods and meta-analyses remain less common, with 12 studies, or 10.9%, and 5 studies, or 4.5%, respectively. Taken together, conceptual contributions, reviews and meta-analyses account for 52.7% of the corpus, indicating that the field remains slightly more oriented towards theoretical argumentation and secondary synthesis than towards direct empirical observation of AI recruitment practices in organizational contexts. This composition helps explain why claims related to efficiency and adoption are more consistently documented than claims requiring prospective criterion-validation designs. This pattern is also reflected in the controversy matrix, where claims requiring direct predictive-validation evidence remain contested or weakly supported, unlike efficiency and adoption-related claims.

The geographical distribution further constrains the evidentiary reach of the field. Studies originating from, or focused on, the United States account for 38 contributions, representing 34.5% of the corpus, while the United Kingdom, Germany, and the Netherlands collectively add 20 contributions. Non-Western institutional contexts remain marginal: India contributes 3 studies, Morocco 4, and the rest of Africa and the Middle East are virtually absent. This concentration matters because the legitimation mechanisms that sustain AI recruitment adoption, including regulatory permissiveness, competitive mimicry among firms, and the diffusion of professional norms, operate differently across institutional environments (Brewster, 1999; Pan et al., 2022). The claims advanced in this review are therefore explicitly

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

bounded by the predominantly Western and Anglophone character of the evidence on which they rest.

Table 2: Positioning Against Prior Systematic Reviews

Dimension	***Köchling & Wehner (2020)***	***Hunkenschroer & Luetge (2022)***	***Meijerink & Bondarouk (2023)***	***Present review***
Analytical scope	Ethical dimension only	Ethical dimension only	HRM tech broadly	Legitimation-validation paradox
Corpus	60 articles	56 articles	75 articles	110 articles
Central question	How does ADM discriminate?	What ethics issues arise?	How does AI affect employees?	Why are unvalidated tools adopted?
Synthesis method	Thematic	Thematic	Thematic	Controversy-mapping
Propositional output	Research agenda	Research agenda	Implications	5 falsifiable propositions
Stance toward AI tools	Governance/ethics-focused framing	Governance/ethics-focused framing	Governance/ethics-focused framing	Interrogates premise of tools

Source: Authors

Table 2 positions the present review against the three closest prior syntheses. The critical distinction is not scope or corpus size, but analytical stance. Prior reviews accepted the functional premise of AI recruitment tools by asking how they create ethical problems, how organizations adopt them, or how they affect employees, without questioning whether the foundational performance claims of these tools justify the scholarly attention they have received. The present review departs from this pattern by treating the relationship between institutional legitimacy and empirical validation as the primary object of inquiry. This shift in analytical stance, from accepting the premise to interrogating it, constitutes the central repositioning that this article offers to the field.

5. The Legitimation-Validation Paradox

The analytical core of this review is not organized around thematic categories describing what the literature says about AI in recruitment, but around a single theoretical puzzle: how have AI recruitment tools achieved widespread organizational adoption and sustained scholarly attention while independent evidence for their predictive validity remains essentially absent? The controversy matrix presented in Figure 4 maps eight recurrent empirical claims across the corpus by consensus status and evidence level, providing the evidentiary foundation for the analysis that follows. The operational coding rules are reported in Appendix D.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

Figure 4. Controversy matrix mapping eight empirical claims by consensus status and evidence level.



Source: Authors

The first task is to establish the scale and nature of the validation deficit. The controversy matrix reveals a sharp asymmetry. The claim that AI screening tools improve operational efficiency, by reducing screening time and recruitment costs, reaches convergent status and is supported by Level 1 evidence from multiple independent studies (Albert, 2019; Black & van Esch, 2020; Upadhyay & Khandelwal, 2018). By contrast, the claim that AI screening tools improve selection quality, measured through criterion validity against subsequent job performance, reaches only contested status and is supported by Level 2 evidence from individual studies that have not been independently replicated and that suffer from methodological limitations, principally the circularity of training predictive models on historical hiring decisions made by human recruiters (Van den Broek et al., 2021). This distinction is crucial. Efficiency and validity are logically independent properties. A tool that screens 10,000 applications in one hour is efficient; whether the candidates it selects perform better in their roles than those selected by other means is a separate empirical question that efficiency metrics cannot answer.

The personnel-selection literature has long grappled with precisely this distinction. A century of psychometric research has established demanding validation standards for assessment instruments, requiring evidence that selection methods predict job performance with measurable accuracy across populations (Ployhart et al., 2017; Society for Industrial and Organizational Psychology, 2018). Structured interviews, cognitive-ability tests, and work-sample tests have been subjected to extensive meta-analytic scrutiny that quantifies their predictive validity (Kuncel et al., 2013). No equivalent body of independent validation evidence exists for commercial AI recruitment tools. Sajjadiani et al. (2019) showed that machine-learning models can extract predictive features from applicants' work histories, but their study used archival data from a single employer and has not been independently replicated across organizational contexts. Pessach et al. (2020) developed a prescriptive matching algorithm, but its evaluation relied on internal data rather than prospective validation. The vendor community has not published independent criterion-validity studies in peer-reviewed outlets. The evidence reviewed here suggests that the validation deficit should not be treated merely as a temporary research lag; it may reflect a more durable institutional condition in which commercial adoption has outpaced independent scientific scrutiny.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

If evidence does not explain adoption, what accounts for it? The analytical framework advanced here identifies four institutional mechanisms that generate and sustain the legitimacy of AI recruitment tools in the absence of validation evidence. These mechanisms are derived from the corpus through controversy mapping rather than imposed a priori, although their articulation is informed by institutional theory and by the literature on organizational legitimation strategies (DiMaggio & Powell, 1983; Suchman, 1995). They are not supported with equal evidentiary strength: mimetic isomorphism and regulatory ambiguity receive comparatively stronger support, whereas normative professionalization and vendor rhetoric capture are more inferential and should be treated as theoretically grounded mechanisms requiring further empirical testing.

The first mechanism is mimetic isomorphism. Organizations adopt AI recruitment tools because peer organizations have adopted them, generating competitive anxiety in which non-adoption is perceived as a signal of strategic backwardness rather than prudent skepticism. Pan et al. (2022) provided direct evidence that organizational size and industry sector, both proxies for competitive visibility, significantly predict AI recruitment adoption independently of any assessment of the tools' effectiveness. Tambe et al. (2019) observed that pressure to adopt AI in HR frequently precedes any internal evaluation of whether the technology addresses a genuine organizational need. This mimetic dynamic creates a self-reinforcing cycle: adoption by prominent organizations confers legitimacy on the technology, which increases adoption pressure on other organizations, which further strengthens legitimacy, independently of any evidence concerning performance outcomes. The mechanism explains why validation evidence is not demanded: in an isomorphic adoption process, the relevant question is not "does this work?" but "are others using it?"

The second mechanism is coercive regulatory ambiguity. The regulatory environment surrounding AI in recruitment is characterized not by prohibition or obligation, but by ambiguity. The European Union AI Act classifies certain employment-related AI applications as high-risk but does not impose specific validation standards for recruitment algorithms. The United States lacks federal legislation governing AI in hiring, with only scattered municipal ordinances, most notably New York City's Local Law 144, attempting to impose audit requirements. The Moroccan context illustrates this pattern in emerging economies: Law 09-08 of CNDP provides a general data-protection framework but contains no provisions specific to algorithmic decision-making in employment (El Mnouer et al., 2023). This regulatory ambiguity functions as a form of coercive legitimation: the absence of prohibition is interpreted as permission, and the absence of validation requirements removes the institutional pressure that would otherwise compel vendors and employers to demonstrate effectiveness. Kim (2017) showed that existing anti-discrimination law was designed for human decision-makers and struggles to address algorithmic discrimination, further reducing the regulatory friction that might otherwise slow the adoption of unvalidated tools.

The third mechanism is normative professionalization pressure. The HR profession has long been subject to pressure to demonstrate strategic relevance and data-driven capability (Angrave et al., 2016; Marler & Boudreau, 2017). AI adoption in recruitment offers HR leaders a visible means of signaling analytical sophistication and strategic alignment with broader digital-transformation agendas. Charlwood and Guenole (2022) analyzed how AI paradoxes challenge HR professional identity, finding that the profession's response has been to reframe AI adoption as a competency requirement rather than as a choice requiring evidence-based justification. This normative pressure operates through professional associations, industry conferences, and consulting ecosystems that propagate AI adoption as a marker of professional currency. The mechanism transforms the adoption decision from a cost-benefit calculation requiring validation evidence into a performance of professional identity requiring conformity with emerging norms. Paramita et al. (2024) documented how

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND
IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

this pressure manifests at the practitioner level, observing that recruiters who resist AI tools risk being perceived by their organizations as technologically backward, regardless of whether the tools demonstrably improve hiring outcomes.

The fourth mechanism is vendor rhetoric capture. The AI recruitment technology market is characterized by strong information asymmetries between vendors, who possess technical knowledge about their systems' capabilities and limitations, and purchasing organizations, which usually lack the data-science expertise required to evaluate vendor claims independently. Vendor rhetoric capture refers to a legitimation mechanism in which vendors' performance claims, framed through technical and managerial language, become accepted as decision-relevant evidence despite the absence of independent validation. Raghavan et al. (2020) found that hiring-algorithm vendors make extensive claims about bias mitigation and predictive accuracy that are not supported by published validation data. Lebovitz et al. (2021) showed that the ground truth against which AI tools are evaluated is itself a socially constructed artifact, raising the question of what independent standard vendors could validate against even if they were motivated to do so. Vendor rhetoric capture explains a counterintuitive feature of the AI recruitment market: greater computational opacity may facilitate rather than hinder adoption because opacity prevents purchasers from discovering the limitations that transparency would expose, allowing the vendor's promotional framing to operate without challenge.

A final analytical observation concerns the possible role of academic research in stabilizing the legitimation-validation paradox. This claim should not be read as suggesting that critical scholarship directly legitimates AI recruitment tools, since studying a phenomenon critically is not equivalent to endorsing it. Rather, the argument is more limited: when the literature primarily examines how AI recruitment should be governed, adopted, or ethically constrained, while paying less attention to whether these tools have been independently validated, it may unintentionally contribute to treating their functional relevance as an implicit premise. The prior reviews by Köchling and Wehner (2020), Hunkenschroer and Luetge (2022), and Meijerink and Bondarouk (2023) illustrate this tendency, not as a flaw in their scholarship, but as evidence of how the field has been organized.

The controversy matrix (Figure 4) makes this structural feature of the field visible. Among the eight empirical claims mapped, the two most fundamental claims, namely that AI tools improve selection quality and that video-based AI predicts job performance, receive the weakest evidentiary support. Yet these are precisely the claims on which the practical relevance of subsequent ethical, organizational, and governance research depends. If AI recruitment tools do not improve selection quality, the urgency of ethical and organizational questions diminishes considerably: the tools become costly administrative conveniences rather than consequential decision-making systems requiring governance. The field's allocation of scholarly attention, heavily concentrated on ethics and adoption dynamics rather than foundational validity testing, therefore reflects and reinforces the legitimation-validation paradox identified in this review.

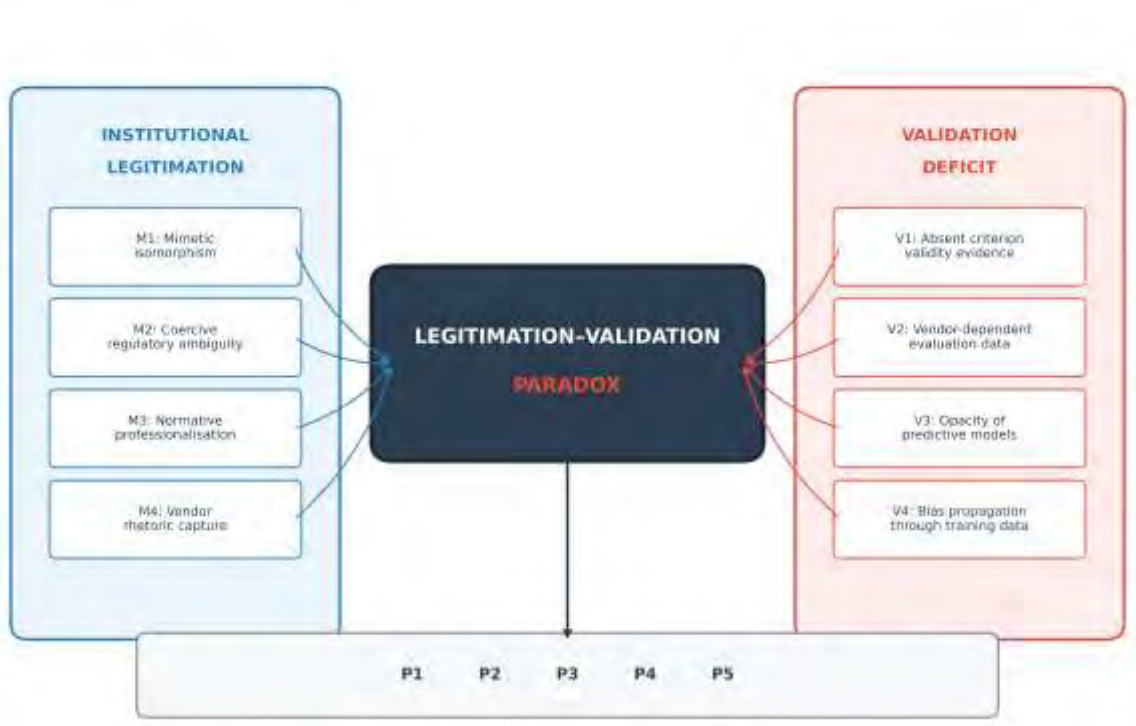
6. Paradox Model and Propositional Agenda

The preceding analysis identifies a legitimation-validation paradox in AI-driven talent acquisition and links it to four institutional mechanisms operating within a permissive academic environment. Figure 5 formalizes this analysis as a conceptual model in which institutional legitimation drivers and validation deficits interact to sustain the paradox, generating five propositions that specify non-obvious and empirically testable predictions. These propositions are designed to be falsifiable: each identifies a relationship, a mechanism, and the conditions under which the proposition would be refuted. Operationally, opacity refers

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

to limited disclosure of model logic, input weighting, and decision rules; scholarly legitimation refers to the accumulation of academic attention that may signal field relevance independently of validation evidence; and mimetic motivation refers to adoption rationales grounded in competitor imitation rather than internal performance evaluation. Possible empirical proxies include explainability disclosures for opacity, post-regulation market shifts for regulatory arbitrage, publication and citation volume for scholarly legitimation, longitudinal recruiter narratives for identity reconstruction, and adoption rationales referencing competitors for mimetic motivation (Mitchell et al., 2019).

Figure 5: Institutional mechanisms, validation deficits, and derived propositions.



Source: Authors

Proposition 1: Opacity-Adoption Paradox.

AI recruitment tools characterized by greater computational opacity achieve higher organizational adoption rates than functionally equivalent tools offering greater interpretive transparency, because opacity prevents purchasers from identifying the performance limitations that transparency would expose, enabling vendor rhetoric (M4) to operate without challenge. Falsification condition: this proposition is disconfirmed if, after controlling for marketing expenditure and vendor reputation, transparent tools achieve adoption rates equal to or higher than opaque alternatives in matched organizational samples.

Proposition 2: Regulatory Arbitrage.

Regulatory frameworks requiring algorithmic transparency in recruitment, such as provisions of the European Union AI Act, accelerate the deployment of less transparent AI tools in unregulated or weakly regulated jurisdictions because vendors facing compliance costs in regulated markets redirect marketing and deployment resources toward jurisdictions where regulatory ambiguity (M2) permits adoption without validation requirements. Falsification condition: this proposition is disconfirmed if the introduction of transparency mandates in one jurisdiction does not produce measurable increases in opaque-tool deployment in jurisdictions lacking equivalent regulation.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

Proposition 3: Scholarly Legitimation Effect.

The volume of academic publications examining the ethical and organizational implications of a specific AI recruitment tool is positively correlated with that tool's subsequent market adoption, independently of any published validation evidence for the tool, because scholarly attention functions as an unintended signal of technological legitimacy that enters organizational decision-making through consulting reports, industry publications, and professional networks. Falsification condition: this proposition is disconfirmed if academic citation patterns show no relationship with vendor market share after controlling for marketing expenditure, firm size, and regulatory endorsement.

Proposition 4: Identity Reconstruction.

Professional resistance to AI recruitment tools among experienced recruiters decreases over time not through resolution of the automation-augmentation tension, but through narrative reconstruction that reframes compliance with algorithmic recommendations as a form of professional expertise, because normative professionalization pressures (M3) incentivize identity adaptation over sustained resistance (Raisch & Krakowski, 2021). Falsification condition: this proposition is disconfirmed if longitudinal data show that decreased resistance is explained by improved trust based on observed tool accuracy rather than by narrative reframing of the professional role.

Proposition 5: Mimetic Decoupling.

Organizations that adopt AI recruitment tools through mimetic isomorphism (M1) rather than evidence-based evaluation exhibit greater decoupling between formal adoption, meaning acquisition of the tool, and substantive use, meaning allowing the tool to influence consequential hiring decisions, because mimetically motivated adoption satisfies legitimacy demands without requiring genuine operational integration. Falsification condition: this proposition is disconfirmed if mimetically motivated adopters show levels of algorithmic influence on actual hiring decisions equivalent to those of evidence-motivated adopters.

These five propositions share a common architecture: each identifies a non-obvious empirical prediction, specifies the institutional mechanism producing the predicted relationship, and defines the evidentiary conditions under which the prediction would be falsified. This architecture is designed to resist the criticism, appropriately directed at several prior frameworks in this domain, that propositions in review articles often function as structured restatements of existing intuitions rather than genuine additions to theoretical knowledge. Each proposition predicts something that an informed reader might not expect and could plausibly imagine being false, thereby meeting the basic criterion of scientific informativeness that trivial or tautological propositions fail to satisfy.

7. Discussion

This review advances one central argument: the fundamental problem of AI in talent acquisition is not the set of ethical, organizational, and technological issues that the existing literature has catalogued, but the paradox that these issues have received extensive scholarly attention while the foundational question of whether AI recruitment tools improve selection quality remains unanswered. The legitimation-validation paradox is therefore both an empirical phenomenon, documented through the controversy-mapping analysis of 110 publications, and a theoretical construct that generates non-obvious predictions amenable to future empirical testing.

The theoretical contribution of this reframing operates at three levels. At the level of the AI recruitment field specifically, the review repositions the research agenda from cataloguing the

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND
IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

implications of an assumed technology to interrogating the conditions under which an unvalidated technology has acquired institutional authority. This repositioning has direct practical consequences: if the validity of AI recruitment tools cannot be demonstrated, then the entire apparatus of ethical governance, bias auditing, and fairness testing constructed by the field rests on an unexamined premise. The ethical question of whether AI recruitment is fair presupposes that these tools exert sufficient influence on outcomes to make fairness a meaningful concern. If the tools do not predict job performance, their influence on hiring outcomes may be less consequential than assumed, and the fairness debate, although intellectually legitimate, may rest on an unverified empirical condition.

At the level of institutional theory, this review presents AI recruitment as a contemporary case study of how technologies acquire organizational legitimacy under conditions of high epistemic uncertainty. The four mechanisms identified, namely mimetic isomorphism, regulatory ambiguity, normative professionalization, and vendor rhetoric capture, are not specific to this setting. They constitute a general model of technological legitimation that may apply to other domains in which adoption outpaces validation, including algorithmic credit scoring, predictive policing, and AI-assisted medical diagnosis. The propositions derived from the model, particularly the opacity-adoption paradox (P1) and the scholarly legitimation effect (P3), identify dynamics that have not yet been formalized in institutional theory and that could motivate empirical investigation across multiple technological domains.

At the methodological level, the review demonstrates the analytical value of controversy mapping as an alternative to conventional thematic synthesis for fields characterized by contested empirical claims and asymmetric evidence. Thematic synthesis, as commonly practiced, harmonizes findings into coherent categories. This is useful when the objective is consolidation, but counterproductive when the most theoretically informative feature of a literature lies in its internal contradictions and evidentiary gaps. The controversy matrix (Figure 4) makes visible what thematic synthesis would tend to smooth over: the sharp disjunction between convergent evidence supporting efficiency claims and contested or absent evidence supporting validity claims. This methodological choice is therefore not merely a procedural alternative; it enables a different form of theoretical work.

The limitations of this review require explicit acknowledgment. The corpus is overwhelmingly Western and Anglophone, and the institutional mechanisms identified may operate differently in non-Western settings where regulatory traditions, labour-market structures, and professional norms differ substantially. Although controversy mapping is well suited to the analytical objectives of this review, it involves interpretive judgments in classifying consensus status and evidence levels, and other researchers may classify some claims differently. Three further limitations should be noted: the exclusion of grey literature may omit relevant vendor, regulatory, or practitioner evidence; publication bias may overrepresent studies reporting salient or positive findings; and the category of AI recruitment tools remains technically heterogeneous, combining résumé screening, matching systems, chatbots, and video-interview algorithms. The critical stance adopted toward the field's engagement with AI recruitment tools could also be perceived as dismissive of the genuine ethical and organizational challenges these technologies create. This is not the intention. The ethical questions are real and important. The argument is not that they should be abandoned, but that they should be pursued with greater attention to whether their foundational empirical premise is warranted.

8. Conclusion

AI recruitment tools have attained a degree of institutional legitimacy that is not supported by independent validation evidence. This legitimation-validation paradox, sustained by mimetic

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

isomorphism, regulatory ambiguity, normative professionalization pressures, and vendor rhetoric capture, constitutes the central finding of this critical systematic review of 110 publications. Five propositions formalize non-obvious predictions concerning the opacity-adoption relationship, regulatory arbitrage dynamics, the unintended legitimating function of scholarly attention, professional identity reconstruction, and the decoupling of formal adoption from substantive use.

The practical implications are direct. Organizations deploying or considering AI recruitment tools should demand independent criterion-validity evidence before committing to technologies whose efficiency is documented but whose predictive value remains unproven. At a minimum, organizations should document the tool's intended use and require vendor disclosure of validation evidence; at an intermediate level, they should conduct internal bias and performance audits; at an advanced level, they should commission independent criterion-validation studies before using AI outputs in consequential hiring decisions. Regulators designing governance frameworks should recognize that transparency requirements, although necessary, may generate arbitrage dynamics that redistribute rather than reduce the risks of unvalidated algorithmic hiring. Scholars studying AI in recruitment should examine whether their analytical framing implicitly accepts assumptions about technological functionality that the evidence does not yet support, and should prioritize independent validation research as a precondition for the ethical and organizational analyses that have so far dominated the field.

The broader message is one of analytical caution. The appeal of a topical phenomenon, the institutional incentives to study emerging technologies, and the genuine importance of the ethical questions at stake have produced a scholarly field in which commentary and governance debates have developed faster than foundational validation evidence. Future research should prioritize longitudinal adoption studies, cross-national comparisons of regulatory regimes, independent validity audits, ethnographies of algorithmic procurement, and bibliometric analyses of the scholarly legitimation effect (Raji et al., 2020). Recognizing this condition is not a counsel of despair, but a call for reorientation: toward validation research that tests the claims on which everything else depends, toward institutional analysis that explains why unvalidated tools acquire authority, and toward scholarly practice that interrogates its own role in legitimating the technologies it studies.

References:

(1). Acikgoz, Y., Davison, K. H., Compagnone, M., & Laske, M. (2020). Justice perceptions of AI in selection. *International Journal of Selection and Assessment, 28*(4), 399-416.

(2). Albert, E. T. (2019). AI in talent acquisition: A review of AI-applications used in recruitment and selection. *Strategic HR Review, 18*(5), 215-221.

(3). American Educational Research Association, American Psychological Association, & National Council on Measurement in Education. (2014). *Standards for educational and psychological testing*. American Educational Research Association.

(4). Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. *Human Resource Management Journal, 26*(1), 1-11.

(5). Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 52-115.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

(6). Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3-30.
(7). Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review, 104*(3), 671-732.
(8). Bellamy, R. K. E., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K., Lohia, P., Martino, J., Mehta, S., Mojsilović, A., Nagar, S., Ramamurthy, K. N., Richards, J., Saha, D., Sattigeri, P., Singh, M., Varshney, K. R., & Zhang, Y. (2019). AI Fairness 360: An extensible toolkit for detecting, understanding, and mitigating unwanted algorithmic bias. *IBM Journal of Research and Development*, 63(4/5), 4:1-4:15.
(9). Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons, 63*(2), 215-226.
(10). Bondarouk, T., Parry, E., & Furtmueller, E. (2017). Electronic HRM: Four decades of research on adoption and consequences. *International Journal of Human Resource Management, 28*(1), 98-131.
(11). Brewster, C. (1999). Strategic human resource management: The value of different paradigms. *Management International Review, 39*(S3), 45-64.
(12). Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research, 81*, 77-91.
(13). Campion, M. C., Campion, M. A., Campion, E. D., & Reider, M. H. (2016). Initial investigation into computer scoring of candidate essays for personnel selection. *Journal of Applied Psychology, 101*(7), 958-975.
(14). Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of AI? *Human Resource Management Journal, 32*(4), 729-742.
(15). Dastin, J. (2018, October 10). Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters*.
(16). Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114-126.
(17). DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review, 48*(2), 147-160.
(18). Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management Journal, 30*(1), 114-132.
(19). El Mnouer, O., Katfi, A., Katfi, H., & Mrhari, A. (2023). AI and recruitment in Morocco: Innovative frontiers for optimizing the collaborator experience. *International Journal of Accounting, Finance, Auditing, Management and Economics, 4*(6-2), 223-238.
(20). European Parliament. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Official Journal of the European Union, L 2024/1689*.
(21). Feldman, M. S., & Pentland, B. T. (2003). Reconceptualizing organizational routines as a source of flexibility and change. *Administrative Science Quarterly, 48*(1), 94-118.
(22). Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: Reviewing the perils for organisations and employees. *European Journal of Information Systems, 31*(3), 410-435.
(23). Gilliland, S. W. (1993). The perceived fairness of selection systems: An organizational justice perspective. *Academy of Management Review, 18*(4), 694-734.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

(24). Glikson, E., & Woolley, A. W. (2020). Human trust in AI: Review of empirical research. *Academy of Management Annals, 14*(2), 627-660.
(25). Hmoud, B., & Laszlo, V. (2019). Will AI take over human resources recruitment and selection? *Network Intelligence Studies, 7*(13), 21-30.
(26). Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., ... Vedel, I. (2018). *Mixed Methods Appraisal Tool (MMAT), version 2018*. Canadian Intellectual Property Office.
(27). Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics, 178*, 977-1007.
(28). Jarrahi, M. H. (2018). AI and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577-586.
(29). Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366-410.
(30). Kim, P. T. (2017). Data-driven discrimination at work. *William & Mary Law Review, 58*(3), 857-936.
(31). Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. *Business Research, 13*(3), 795-848.
(32). Kuncel, N. R., Klieger, D. M., Connelly, B. S., & Ones, D. S. (2013). Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis. *Journal of Applied Psychology, 98*(6), 1060-1072.
(33). Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33(1), 159–174.
(34). Langer, M., König, C. J., & Papathanasiou, M. (2019). Highly automated job interviews: Acceptance under the influence of stakes. *International Journal of Selection and Assessment, 27*(3), 217-234.
(35). Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what. *MIS Quarterly, 45*(3), 1615-1646.
(36). Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90-103.
(37). Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *International Journal of Human Resource Management, 28*(1), 3-26.
(38). Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys, 54*(6), 1-35.
(39). Meijerink, J., & Bondarouk, T. (2023). The force of HRM technology and AI on employees: A systematic review. *International Journal of Human Resource Management, 34*(5), 987-1022.
(40). Miles, M. B., Huberman, A. M., & Saldaña, J. (2019). *Qualitative data analysis: A methods sourcebook* (4th ed.). Sage.
(41). Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebru, T. (2019). Model cards for model reporting. *Proceedings of the Conference on Fairness, Accountability, and Transparency*, 220-229.
(42). Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society, 3*(2), 1-21.
(43). Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149-167.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

(44). Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science, 3*(3), 398-427.
(45). Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71.
(46). Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of AI in employee recruitment: The influence of contextual factors. *International Journal of Human Resource Management, 33*(6), 1125-1147.
(47). Paramita, D., Okwir, S., & Nuur, C. (2024). AI in talent acquisition: Exploring organisational and operational dimensions. *International Journal of Organizational Analysis, 32*(11), 108-131.
(48). Pessach, D., Singer, G., Avrahami, D., Ben-Gal, H. C., Shmueli, E., & Ben-Gal, I. (2020). Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming. *Decision Support Systems, 134*, 113290.
(49). Ployhart, R. E., Schmitt, N., & Tippins, N. T. (2017). Solving the supreme problem: 100 years of selection and recruitment at the Journal of Applied Psychology. *Journal of Applied Psychology, 102*(3), 291-304.
(50). Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 469-481.
(51). Raisch, S., & Krakowski, S. (2021). AI and management: The automation-augmentation paradox. *Academy of Management Review, 46*(1), 192-210.
(52). Raji, I. D., Smart, A., White, R. N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D., & Barnes, P. (2020). Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. *Proceedings of the Conference on Fairness, Accountability, and Transparency*, 33-44.
(53). Sajjadiani, S., Sojourner, A. J., Kammeyer-Mueller, J. D., & Mykerezi, E. (2019). Using machine learning to translate applicant work history into predictors of performance and turnover. *Journal of Applied Psychology, 104*(10), 1207-1225.
(54). Scott, W. R. (2014). *Institutions and organizations: Ideas, interests, and identities* (4th ed.). Sage Publications.
(55). Society for Industrial and Organizational Psychology. (2018). Principles for the validation and use of personnel selection procedures (5th ed.). *Industrial and Organizational Psychology*, 11(S1), 1-97.
(56). Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics, 87*(3), 355-374.
(57). Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. *Human Resource Management Review, 25*(2), 216-231.
(58). Strohmeier, S. (2007). Research in e-HRM: Review and implications. *Human Resource Management Review, 17*(1), 19-37.
(59). Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review, 20*(3), 571-610.
(60). Suddaby, R., Bitektine, A., & Haack, P. (2017). Legitimacy. *Academy of Management Annals, 11*(1), 451-478.
(61). Tambe, P., Cappelli, P., & Yakubovich, V. (2019). AI in human resources management: Challenges and a path forward. *California Management Review, 61*(4), 15-42.
(62). Townley, B. (1993). Foucault, power/knowledge, and its relevance for human resource management. *Academy of Management Review, 18*(3), 518-545.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

(63). Upadhyay, A. K., & Khandelwal, K. (2018). Applying AI: Implications for recruitment. *Strategic HR Review, 17*(5), 255-258.
(64). Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. *MIS Quarterly, 45*(3), 1557-1580.
(65). Veale, M., & Borgesius, F. Z. (2021). Demystifying the Draft EU Artificial Intelligence Act: Analysing the good, the bad, and the unclear elements of the proposed approach. *Computer Law Review International, 22*(4), 97-112.
(66). Venturini, T. (2010). Diving in magma: How to explore controversies with actor-network theory. *Public Understanding of Science, 19*(3), 258-273.
(67). Wachter, S., Mittelstadt, B., & Russell, C. (2018). Counterfactual explanations without opening the black box: Automated decisions and the GDPR. *Harvard Journal of Law & Technology, 31*(2), 841-887.
(68). Weick, K. E. (1995). *Sensemaking in organizations*. Sage.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

Appendix A: Database-specific search strategy and deduplication protocol

A.1: Database-specific search log

Database	Search string / semantic equivalent	Field	Date	Records	source occurrences
Scopus	TITLE-ABS-KEY(("AI" OR "artificial intelligence" OR "machine learning" OR "algorithm" OR "automat*") AND ("recruit*" OR "hiring" OR "selection" OR "talent acquisition" OR "staffing"))	Title, abstract, keywords	January-March 2025	809	88
Web of Science	TS=(("AI" OR "artificial intelligence" OR "machine learning" OR "algorithm" OR "automat*") AND ("recruit*" OR "hiring" OR "selection" OR "talent acquisition" OR "staffing"))	Topic: title, abstract, author keywords, Keywords Plus	January-March 2025	506	55
EBSCO Business Source	AB/Title/Subject: ("AI" OR "artificial intelligence" OR "machine learning" OR "algorithm" OR "automat*") AND ("recruit*" OR "hiring" OR "selection" OR "talent acquisition" OR "staffing")	Title, abstract, subject terms	January-March 2025	506	55
PsycINFO	Abstract/Title/Subject: ("AI" OR "artificial intelligence" OR "machine learning" OR "algorithm" OR "automat*") AND ("recruit*" OR "hiring" OR "selection" OR "talent acquisition" OR "staffing")	Title, abstract, subject terms	January-March 2025	138	15
IEEE Xplore	("AI" OR "artificial intelligence" OR "machine learning" OR "algorithm" OR "automat*") AND ("recruit*" OR "hiring" OR "selection" OR "talent acquisition" OR "staffing")	Metadata: title, abstract, index terms	January-March 2025	165	18
JSTOR	("AI" OR "artificial intelligence" OR "machine learning" OR "algorithm" OR "automat*") AND ("recruit*" OR "hiring" OR "selection" OR "talent acquisition" OR "staffing")	Full text and metadata	January-March 2025	64	7
Google Scholar	("artificial intelligence" OR "machine learning" OR algorithm) ("recruitment" OR "hiring" OR "talent acquisition" OR "selection")	All fields	January-March 2025	193	21
ProQuest Dissertations	("AI" OR "artificial intelligence" OR "machine learning" OR "algorithm") AND ("recruitment" OR "hiring" OR "selection" OR "talent acquisition")	Title, abstract, subject terms	January-March 2025	9	1
Cairn.info	("intelligence artificielle" OR "IA" OR "algorithme") AND ("recrutement" OR "sélection" OR "acquisition de talents")	Title, résumé, full text	January-March 2025	37	4

A.2: PRISMA flow and deduplication summary

PRISMA step	n
Records identified through database searching	2427
Duplicates removed	329
Records after duplicate removal / title-abstract screening	2098
Excluded at title/abstract screening	1583
Full-text assessed	515
Excluded after full-text assessment	315
Quality appraisal pool	200
Excluded after MMAT or source-appropriate quality/relevance assessment	58
Above quality threshold	142
Additional scope / redundancy / saturation pruning needed	44
Database-search studies retained after pruning	98
Supplementary citation tracking additions	12
Final analytical corpus	110

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

A.3: Deduplication protocol

Element	Value / rule
Records before deduplication	2,427
Duplicates removed	329
Records after duplicate removal	2,098
Software/tool used	Microsoft Excel
Matching criteria	DOI where available; normalized title; first author; publication year; journal/source title; and manual comparison of bibliographic variants.
Manual verification	Potential duplicates were manually checked before removal. Records were not excluded solely because of similar titles when publication type, venue, year, or version differed. Where conference, working-paper, and journal versions overlapped, the peer-reviewed or most complete version was retained.
Rule for missing DOI	When DOI was missing, deduplication relied on title similarity, first author, year, source title, and manual verification of the reference.
Rule for multiple database occurrence	Records retrieved from several databases were retained once in the screening file, while all database occurrences were preserved in the source-tracking field.
Rule for uncertainty	Ambiguous cases were retained for title-and-abstract screening rather than removed at the deduplication stage.

The PRISMA table includes a pruning step after quality appraisal: 142 studies above the quality threshold were reduced by 44 scope/redundancy/coding-stability exclusions, leaving 98 database-search studies; 12 supplementary citation-tracking studies were then added, producing the final corpus of 110 publications.

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

Appendix B: Final corpus of included studies

ID	Year	Reference	DOI
1	2019	Hmoud, B., & Laszlo, V. (2019). Will artificial intelligence take over human resources recruitment and selection? Network Intelligence Studies, 7(13), 21-30.	N/A
2	2019	Van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. Computers in Human Behavior, 90, 215-222.	10.1016/j.chb.2018.09.009
3	2018	Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. Strategic HR Review, 17(5), 255-258.	10.1108/SHR-07-2018-0051
4	2022	Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. International Journal of Organizational Analysis, 30(6), 1771-1782.	10.1108/IJOA-07-2020-2291
5	2019	Albert, E. T. (2019). AI in talent acquisition: A review of AI-applications used in recruitment and selection. Strategic HR Review, 18(5), 215-221.	10.1108/SHR-04-2019-0024
6	2019	Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15-42.	10.1177/0008125619867910
7	2024	Paramita, D., Okwir, S., & Nuur, C. (2024). Artificial intelligence in talent acquisition: exploring organisational and operational dimensions. International journal of organizational analysis, 32(11), 108-131.	10.1108/IJOA-09-2023-3992
8	2019	Nawaz, N. (2019). Artificial intelligence interchange human intervention in the recruitment process in Indian software industry. International Journal of Advanced Trends in Computer Science and Engineering, 8(4), 1433-1442.	N/A
9	2020	Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? Business Horizons, 63(2), 215-226.	10.1016/j.bushor.2019.12.001
10	2018	Geetha, R., & Bhanu, S. R. D. (2018). Recruitment through artificial intelligence: A conceptual study. International Journal of Mechanical Engineering and Technology, 9(7), 63-70.	N/A
11	2020	Suen, H. Y., Hung, K. E., & Lin, C. L. (2020). TensorFlow-based automatic personality recognition used in asynchronous video interviews. IEEE Access, 8, 183408-183420.	10.1109/ACCESS.2020.3029041
12	2019	Suen, H. Y., Chen, M. Y., & Lu, S. H. (2019). Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes? Computers in Human Behavior, 98, 93-101.	10.1016/j.chb.2019.04.012
13	2019	Gonzalez, M. F., Capman, J. F., Oswald, F. L., Theys, E. R., & Tomczak, D. L. (2019). 'Where's the I-O?' Artificial intelligence and machine learning in talent management systems. Personnel Assessment and Decisions, 5(3), 33-44.	10.25035/pad.2019.03.005
14	2020	Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. ACM FAT* Conference, 469-481.	10.1145/3351095.3372828
15	2021	Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. ACM Computing Surveys, 54(6), 1-35.	10.1145/3457607
16	2018	Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. Reuters.	N/A
17	2020	Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. Business Research, 13(3), 795-848.	10.1007/s40685-020-00134-w
18	2019	Langer, M., König, C. J., & Papathanasiou, M. (2019). Highly automated job interviews: Acceptance under the influence of stakes. International Journal of Selection and Assessment, 27(3), 217-234.	10.1111/ijsa.12246
19	2018	Bogen, M., & Rieke, A. (2018). Help wanted: An examination of hiring algorithms, equity, and bias. Upturn.	N/A
20	2001	Straus, S. G., Miles, J. A., & Levesque, L. L. (2001). The effects of videoconference, telephone, and face-to-face media on interviewer and applicant judgments in employment interviews. Journal of Management, 27(3), 363-381.	10.1177/014920630102700306

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

21	2017	McCarthy, J. M., Bauer, T. N., Truxillo, D. M., Anderson, N. R., Costa, A. C., & Ahmed, S. M. (2017). Applicant perspectives during selection: A review addressing 'so what?', 'what's new?', and 'where to next?'. Journal of Management, 43(6), 1693-1725.	10.1177/0149206316681846
22	2000	Ryan, A. M., & Ployhart, R. E. (2000). Applicants' perceptions of selection procedures and decisions: A critical review and agenda for the future. Journal of Management, 26(3), 565-606.	10.1177/014920630002600308
23	1993	Gilliland, S. W. (1993). The perceived fairness of selection systems: An organizational justice perspective. Academy of Management Review, 18(4), 694-734.	10.5465/amr.1993.9402210155
24	2017	Bondarouk, T., Parry, E., & Furtmueller, E. (2017). Electronic HRM: Four decades of research on adoption and consequences. International Journal of Human Resource Management, 28(1), 98-131.	10.1080/09585192.2016.1245672
25	2007	Strohmeier, S. (2007). Research in e-HRM: Review and implications. Human Resource Management Review, 17(1), 19-37.	10.1016/j.hrmr.2006.11.002
26	2017	Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. International Journal of Human Resource Management, 28(1), 3-26.	10.1080/09585192.2016.1244699
27	2016	Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1-11.	10.1111/1748-8583.12090
28	2013	Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. Organizational Research Methods, 16(1), 15-31.	10.1177/1094428112452151
29	1967	Glaser, B. G., & Strauss, A. L. (1967). The discovery of grounded theory: Strategies for qualitative research. Aldine.	N/A
30	1998	Strauss, A., & Corbin, J. (1998). Basics of qualitative research: Techniques and procedures for developing grounded theory (2nd ed.). Sage.	N/A
31	2006	Charmaz, K. (2006). Constructing grounded theory: A practical guide through qualitative analysis. Sage.	N/A
32	2018	Creswell, J. W., & Poth, C. N. (2018). Qualitative inquiry and research design: Choosing among five approaches (4th ed.). Sage.	N/A
33	2019	Miles, M. B., Huberman, A. M., & Saldaña, J. (2019). Qualitative data analysis: A methods sourcebook (4th ed.). Sage.	N/A
34	1985	Lincoln, Y. S., & Guba, E. G. (1985). Naturalistic inquiry. Sage.	N/A
35	1989	Eisenhardt, K. M. (1989). Building theories from case study research. Academy of Management Review, 14(4), 532-550.	10.5465/amr.1989.4308385
36	2018	Yin, R. K. (2018). Case study research and applications: Design and methods (6th ed.). Sage.	N/A
37	2015	Patton, M. Q. (2015). Qualitative research & evaluation methods (4th ed.). Sage.	N/A
38	2006	Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101.	10.1191/1478088706qp063oa
39	2017	Boudreau, J. W., & Cascio, W. F. (2017). Human capital analytics: Why are we not there? Journal of Organizational Effectiveness, 4(2), 119-126.	10.1108/JOEPP-03-2017-0021
40	2020	Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24-42.	10.1007/s11747-019-00696-0
41	2017	Brynjolfsson, E., & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. W.W. Norton.	N/A
42	2015	Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives, 29(3), 3-30.	10.1257/jep.29.3.3
43	2017	Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254-280.	10.1016/j.techfore.2016.08.019
44	2019	Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15-25.	10.1016/j.bushor.2018.08.004
45	2019	Collings, D. G., Mellahi, K., & Cascio, W. F. (2019). Global talent management and performance in multinational enterprises: A multilevel perspective. Journal of Management, 45(2), 540-566.	10.1177/0149206318757018

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

46	2009	Collings, D. G., & Mellahi, K. (2009). Strategic talent management: A review and research agenda. Human Resource Management Review, 19(4), 304-313.	10.1016/j.hrmr.2009.04.001
47	2020	Gallardo-Gallardo, E., Thunnissen, M., & Scullion, H. (2020). Talent management: Context matters. International Journal of Human Resource Management, 31(4), 457-473.	10.1080/09585192.2019.1642645
48	2012	Vaiman, V., Scullion, H., & Collings, D. G. (2012). Talent management decision making. Management Decision, 50(5), 925-941.	10.1108/00251741211227663
49	2015	Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. Human Resource Management Review, 25(2), 216-231.	10.1016/j.hrmr.2015.01.002
50	2011	Parry, E., & Tyson, S. (2011). Desired goals and actual outcomes of e-HRM. Human Resource Management Journal, 21(3), 335-354.	10.1111/j.1748-8583.2010.00149.x
51	1998	Lepak, D. P., & Snell, S. A. (1998). Virtual HR: Strategic human resource management in the 21st century. Human Resource Management Review, 8(3), 215-234.	10.1016/S1053-4822(98)90003-1
52	2017	Ployhart, R. E., Schmitt, N., & Tippins, N. T. (2017). Solving the supreme problem: 100 years of selection and recruitment at the Journal of Applied Psychology. Journal of Applied Psychology, 102(3), 291-304.	10.1037/apl0000081
53	2005	Chapman, D. S., Uggerslev, K. L., Carroll, S. A., Piasentin, K. A., & Jones, D. A. (2005). Applicant attraction to organizations and job choice: A meta-analytic review. Journal of Applied Psychology, 90(5), 928-944.	10.1037/0021-9010.90.5.928
54	2008	Breaugh, J. A. (2008). Employee recruitment: Current knowledge and important areas for future research. Human Resource Management Review, 18(3), 103-118.	10.1016/j.hrmr.2008.07.003
55	2016	Dineen, B. R., & Allen, D. G. (2016). Third party employment branding: Human capital inflows and outflows following 'best places to work' certifications. Academy of Management Journal, 59(1), 90-112.	10.5465/amj.2013.1091
56	2016	Lievens, F., & Slaughter, J. E. (2016). Employer image and employer branding: What we know and what we need to know. Annual Review of Organizational Psychology, 3, 407-440.	10.1146/annurev-orgpsych-041015-062501
57	1998	Barber, A. E. (1998). Recruiting employees: Individual and organizational perspectives. Sage.	N/A
58	2020	Woods, S. A., Ahmed, S., Nikolaou, I., Costa, A. C., & Anderson, N. (2020). Personnel selection in the digital age: A review of validity and applicant reactions, and future research challenges. European Journal of Work and Organizational Psychology, 29(1), 64-77.	10.1080/1359432X.2019.1681401
59	2022	Hickman, L., Thapa, S., Tay, L., Cao, M., & Srinivasan, P. (2022). Text preprocessing for text mining in organizational research: Review and recommendations. Organizational Research Methods, 25(1), 114-146.	10.1177/1094428120971683
60	2016	Chamorro-Premuzic, T., Winsborough, D., Sherman, R. A., & Hogan, R. (2016). New talent signals: Shiny new objects or a brave new world? Industrial and Organizational Psychology, 9(3), 621-640.	10.1017/iop.2016.6
61	2016	Campion, M. C., Campion, M. A., Campion, E. D., & Reider, M. H. (2016). Initial investigation into computer scoring of candidate essays for personnel selection. Journal of Applied Psychology, 101(7), 958-975.	10.1037/apl0000108
62	2019	Sajjadiani, S., Sojourner, A. J., Kammeyer-Mueller, J. D., & Mykerezi, E. (2019). Using machine learning to translate applicant work history into predictors of performance and turnover. Journal of Applied Psychology, 104(10), 1207-1225.	10.1037/apl0000405
63	2013	Kuncel, N. R., Klieger, D. M., Connelly, B. S., & Ones, D. S. (2013). Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis. Journal of Applied Psychology, 98(6), 1060-1072.	10.1037/a0034156
64	2018	Naim, I., Tanveer, M. I., Gildea, D., & Hoque, M. E. (2018). Automated analysis and prediction of job interview performance. IEEE Transactions on Affective Computing, 9(2), 191-204.	10.1109/TAFFC.2016.2614299
65	2016	Nguyen, L. S., & Gatica-Perez, D. (2016). Hirability in the wild: Analysis of online conversational video resumes. IEEE Transactions on Multimedia, 18(7), 1422-1437.	10.1109/TMM.2016.2557058
66	2021	Li, L., Lassiter, T., Oh, J., & Lee, M. K. (2021). Algorithmic hiring in practice: Recruiter and HR professional's perspectives	10.1145/3461702.3462531

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

		on AI use in hiring. AIES '21, 166-176.	
67	2018	Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. Big Data & Society, 5(1), 1-16.	10.1177/2053951718756684
68	2019	Kaibel, C., Koch-Bayram, I., Biemann, T., & Mühlenbock, M. (2019). Applicant perceptions of hiring algorithms—Uniqueness and discrimination experiences as moderators. Academy of Management Proceedings, 2019(1), 18172.	N/A
69	2020	Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. Organizational Behavior and Human Decision Processes, 160, 149-167.	10.1016/j.obhdp.2020.03.008
70	2023	Bankins, S., & Formosa, P. (2023). The ethical implications of artificial intelligence (AI) for meaningful work. Journal of Business Ethics, 185, 725-740.	10.1007/s10551-023-05339-7
71	2020	Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), 627-660.	10.5465/annals.2018.0057
72	2015	Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114-126.	10.1037/xge0000033
73	2019	Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behavior and Human Decision Processes, 151, 90-103.	10.1016/j.obhdp.2018.12.005
74	2021	Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. Computers in Human Behavior, 123, 106878.	10.1016/j.chb.2021.106878
75	1983	Markus, M. L. (1983). Power, politics, and MIS implementation. Communications of the ACM, 26(6), 430-444.	10.1145/358141.358148
76	2003	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.	10.2307/30036540
77	1989	Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.	10.2307/249008
78	1992	Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. Organization Science, 3(3), 398-427.	10.1287/orsc.3.3.398
79	2022	Boudreau, J. W., & Jesuthasan, R. (2022). Work without jobs: How to reboot your organization's work operating system. MIT Press.	N/A
80	2018	Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155-172.	10.1177/1094670517752459
81	2018	Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586.	10.1016/j.bushor.2018.03.007
82	2021	Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review, 46(1), 192-210.	10.5465/amr.2018.0072
83	2021	Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what. MIS Quarterly, 45(3), 1615-1646.	10.25300/MISQ/2021/16564
84	2020	Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. Academy of Management Annals, 14(1), 366-410.	10.5465/annals.2018.0174
85	2020	Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. Human Resource Management Journal, 30(1), 114-132.	10.1111/1748-8583.12258
86	2018	Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. PMLR, 81, 77-91.	N/A
87	2018	Eubanks, V. (2018). Automating inequality: How high-tech tools profile, police, and punish the poor. St. Martin's Press.	N/A
88	2018	Noble, S. U. (2018). Algorithms of oppression: How search engines reinforce racism. NYU Press.	N/A

ISSN: 2658-8455
Volume 7, Issue 07 (2026), pp. 1-33
© Authors: CC BY-NC-ND

89	2018	Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Vayena, E. (2018). AI4People—An ethical framework for a good AI society. Minds and Machines, 28(4), 689-707.	10.1007/s11023-018-9482-5
90	2019	Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389-399.	10.1038/s42256-019-0088-2
91	2023	Meijerink, J., & Bondarouk, T. (2023). The force of HRM technology and AI on employees: A systematic review. International Journal of Human Resource Management, 34(5), 987-1022.	10.1080/09585192.2022.2158873
92	2022	Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence? Human Resource Management Journal, 32(4), 729-742.	10.1111/1748-8583.12433
93	2021	Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. Strategic Management Journal, 42(9), 1600-1631.	10.1002/smj.3322
94	2022	Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: Reviewing the perils for organisations and employees. European Journal of Information Systems, 31(3), 410-435.	10.1080/0960085X.2021.1927213
95	2021	Cheng, M. M., & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. Human Resource Management Review, 31(1), 100698.	10.1016/j.hrmr.2019.100698
96	2021	Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. MIS Quarterly, 45(3), 1557-1580.	10.25300/MISQ/2021/16559
97	2019	Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., Wildhaber, I., & Kasper, G. (2019). The challenges of algorithm-based HR decision-making for personal integrity. Journal of Business Ethics, 160, 377-392.	10.1007/s10551-019-04204-w
98	2017	Kim, P. T. (2017). Data-driven discrimination at work. William & Mary Law Review, 58(3), 857-936.	N/A
99	2017	Ajunwa, I., Crawford, K., & Schultz, J. (2017). Limitless worker surveillance. California Law Review, 105(3), 735-776.	N/A
100	2020	Robert, L. P., Pierce, C., Marquis, L., Kim, S., & Alahmad, R. (2020). Designing fair AI for managing employees in organizations: A review, critique, and design agenda. Human-Computer Interaction, 35(5-6), 545-575.	10.1080/07370024.2020.1735391
101	2022	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.	10.1080/09585192.2021.1879206
102	2020	Pessach, D., Singer, G., Avrahami, D., Ben-Gal, H. C., Shmueli, E., & Ben-Gal, I. (2020). Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming. Decision Support Systems, 134, 113290.	10.1016/j.dss.2020.113290
103	2022	Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. Journal of Business Ethics, 178, 977-1007.	10.1007/s10551-022-05049-6
104	2022	Mirowska, A., & Mesnet, L. (2022). Preferring the devil you know: Potential applicant reactions to artificial intelligence evaluation of interviews. Human Resource Management Journal, 32(2), 364-383.	10.1111/1748-8583.12393
105	2020	Acikgoz, Y., Davison, K. H., Compagnone, M., & Laber, M. (2020). Justice perceptions of artificial intelligence in selection. International Journal of Selection and Assessment, 28(4), 399-416.	10.1111/ijsa.12306
106	2016	Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. California Law Review, 104(3), 671-732.	N/A
107	2023	Boukhris, T., El Khiyari, F., & Ziani, M. (2023). Digital transformation of HR in Morocco: Challenges and opportunities. Journal of North African Studies.	N/A
108	2021	Akesbi, S. (2021). La transformation digitale des pratiques RH dans les entreprises marocaines. Revue Marocaine de Gestion, 15(2), 45-68.	N/A
109	2021	Ben Salah, H. (2021). La digitalisation des pratiques RH dans les entreprises marocaines : étude empirique. Thèse de doctorat, Université Hassan II, Casablanca.	N/A
110	2022	Mansouri, A. (2022). Candidate privacy and AI in recruitment: Emerging challenges in the Moroccan context. African Journal of Business Management, 16(4), 112-125.	N/A

ISSN: 2658-8455
Volume 6, Issue 5 (2025), pp.
© Authors: CC BY-NC-ND

Appendix C: Coding grid and extraction variables

C.1: Core analytical extraction variables

Variable	Operational definition	Coding rule / values
SourceType	Source family.	Empirical; conceptual; review; methodological; contextual.
Discipline	Disciplinary anchoring.	HRM; management; psychology; IS; ethics; law; CS; methods.
Country	Main empirical or institutional context.	Country, Global, or multi-country label.
Method	Study design.	Conceptual; quantitative; qualitative; experimental; mixed; review; methodological.
Cat	Harmonized method category.	Conceptual/theoretical; empirical; review/synthesis; methodological/foundational.
Data	Evidence base.	Survey; interviews; experiment; secondary; internal; archival; video; case; N/A.
Variables	Main constructs or objects studied.	Free-text coding.
Theme	Broad thematic domain.	AI recruitment; bias; ethics; e-HRM; selection; trust; etc.
SubTheme	Specific analytical focus.	Free-text thematic label.
RQ	Research question addressed.	RQ1; RQ2; RQ3; Cross-cutting.
Mechanism	Mechanism supported by the study.	Validation deficit; M1; M2; M3; M4; theory/context.
Controversy	Mapped claim or background category.	C1-C8 or Background/theory.
Consensus	Degree of convergence.	Convergent; contested; weakly supported; emerging; not mapped.
Level	Evidentiary strength.	Level 1; Level 2; Level 3; N/A.

C.2: Traceability and quality-control fields

Field	Purpose
ID	Unique study identifier.
Reference_APA6	Full bibliographic reference.
DOI	Digital Object Identifier when available.
Year	Publication year.
Original	Original descriptor used during corpus construction.
Ranking	Journal/ranking or source-quality descriptor.
Obs	Sample size, observation count, or N/A.
Route	Inclusion route.
Source	Database/source channel.
Quality	Overall quality grade.

C.3: MMAT application rule

Element	Value
MMAT-applicable empirical/mixed-methods records	51
Non-applicable or non-empirical records	59
Records with preliminary score 5	32
Records with preliminary score 4	0
Records with preliminary score 3	4
Records with preliminary score 2	15

Note: Records below the MMAT threshold were not used as empirical support for mapped claims.

C.4: Inter-coder reliability

Stage	Cohen's kappa	Interpretation
Title-and-abstract screening	0.84	Almost perfect agreement
Full-text screening	0.89	Almost perfect agreement

ISSN: 2658-8455
Volume 6, Issue 5 (2025), pp.
© Authors: CC BY-NC-ND

Appendix D. Rules for classifying claims, consensus, and evidence levels

D.1: Consensus-status rules

Consensus status	Coding rule
Convergent	Several independent studies support the claim with broadly consistent conclusions.
Contested	Evidence or interpretation is mixed across studies.
Weakly supported	The claim is present but supported by limited empirical evidence or narrow contexts.
Emerging	The claim is recent, context-dependent, or not yet stabilized.
Not mapped	The source is used for theory, method, or context rather than direct claim classification.

D.2: Evidence-level rules

Evidence level	Coding rule
Level 1	Repeated support across independent studies and/or cross-contextual convergence.
Level 2	Moderate evidence: individual empirical studies, limited replication, or constrained designs.
Level 3	Weaker evidence: mainly conceptual, normative, legal, practitioner-oriented, or insufficiently replicated.
N/A	Background theory or texts not directly mapped to the eight claims.

D.3: Mapped controversy claims

Claim	Operational definition	n	Consensus	Level
C1 Efficiency of screening tools	AI tools reduce screening time, administrative burden, or recruitment costs.	4	Convergent	Level 1
C2 Selection quality / criterion validity	AI tools improve selection quality by predicting subsequent job performance.	7	Contested	Level 2
C3 Video AI and interview prediction	Algorithmic video-interview systems predict interview or job-related performance outcomes.	6	Weakly supported	Level 2
C4 Algorithmic bias and fairness	AI recruitment tools may reproduce, amplify, or mitigate bias and fairness risks.	15	Convergent	Level 1
C5 Candidate acceptance and justice	Candidates and practitioners perceive algorithmic selection through fairness, transparency, and justice concerns.	6	Contested	Level 2
C6 Organizational adoption	Organizations adopt AI recruitment tools due to strategic, competitive, institutional, or operational pressures.	9	Emerging	Level 2
C7 Regulatory accountability	Regulatory and accountability frameworks shape or constrain AI recruitment deployment.	2	Weakly supported	Level 3
C8 Professionalization and HR capability	AI adoption is linked to HR professionalization, analytics capability, and managerial legitimacy.	11	Emerging	Level 3

Note: The n values refer to claim-coded source occurrences, not to the full corpus of 110 publications; theoretical, methodological, and contextual sources are not all mapped to empirical claims.

ISSN: 2658-8455
Volume 6, Issue 5 (2025), pp.
© Authors: CC BY-NC-ND

D.4: Coding-stability and disagreement-resolution rule

Procedure	Rule
Claim definition	Claims were defined abductively by comparing recurrent statements with the article's focus on validation and legitimation.
Evidence-level attribution	Levels were assigned according to independent convergence, methodological rigor, and contextual diversity.
Disagreement resolution	Coding disagreements were resolved through discussion and recoding until consensus was reached.
Coding stability	The final twenty coded studies were checked for changes to claim categories or evidence-level rules; after study 91, no category or rule changed.