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Article

A Systematic Review on AI and Employee Trust: Examining Transparency, Fairness and Human Oversight in HR Decision Making

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Abstract: Adopting AI in HRM revolutionizes the hiring, evaluation and decision-making within companies. However if the procedural justice vision – transparency of algorithms and reduced human involvement in technology – is going to be realized, there are many questions that need to be answered. All these factors are crucial in influencing and building employee attitudes and confidence towards AI HR tools. Objective: This approach has been used consistently to examine the phenomenon of using AI in the HR decision making process, as well as the moderation-mediatory analysis, has been discussed based on the three enabling factors 'transparency, fairness and human supervision'. A detailed job market analysis was also included – in the context of India. In terms of socio-legal and cultural aspects they could be perceived as unusual in terms of AI use in an Indian context. Methods: The search process has been done using Scopus and Web of Science (WoS) based on PRISMA 2020 with search period starting from year 2021-2026 and adding other search engines (JSTOR, SSRN, Google scholar) and peer-reviewed articles. The parameters with respect to which search has been done are literature pertaining to employee trust, transparency research literature, research literature where there is no role of any algorithmic involvement at all and then, the concepts of algorithmic fairness. Quality assessment was done using the CASP evaluation frameworks and Joanna Briggs Institute. topic synthesis and data extraction procedures were applied to analyze the data to get the results of the integration. Results: The total records of the database were 1883 – of which 105 studies were included – final selection. From this comes some of key synthesis implications: there is no clear correlation between algorithmic transparency and employee trust, procedural and/or distributive fairness can be considered as intermediate points in the continuum between algorithmic transparency and employee trust, there are other contextual factors for employee trust some of which are 'human' and some having an impact on the relationship between the elements of AI and employee trust and finally, specifically, the boundary conditions in Indian context are a fragmented regulatory landscape, or digital illiteracy, regional/cultural orientations have impacts on the relationship between the elements of AI and employee trust. Conclusions: Trust in AI for HR decision making is not a relation or tech – but a socio tech challenge and demands more than just tech strategies. The study recommends the use of interdisciplinary thinking; in the AI system the attributes are interconnected and viewed from the perspective of the contextual (moderating) factors, organizational justice theories and its relationship with the following employee indicators: trust. Highlighted policy recommendations/policy implications with a particular emphasis on the implications of the policy for HR practitioners, for policy makers and developers of AI in the unique context of India.
Keywords: Artificial Intelligence, Human Resource Management, Employee Trust, Transparency, Fairness, Human Oversight

1. Introduction

One way AI can shift the paradigm of decision-making in the organization is through its integration into the HR. The nature of the change poses critical algorithmic transparency and considerations around procedural justice and the need for human oversight that would impact the trust their employees place in HR using AI. This systematic literature search paper seeks to overcome some of the constraints mentioned above, bring the findings together of the studies that explored how these qualities of the AI systems affect feelings of fairness and trust and focus on how feelings of organizational justice may act as a mediator between the quality of the AI systems and feelings of fairness and trust and how other factors may act as moderators. Indian employment ‘space' is a prism through which to tease the process for two reasons: one socio-legal, the other cultural.

1.1 Background and Context

With new digital technologies that are disrupting industries throughout the world – Artificial Intelligence (AI), IoT, voice recognition, virtual reality and more – this new Industrial Revolution is underway. Artificial Intelligence (AI) is an area of great interest in human resource management (HRM) as it can be utilized to enhance work productivity, human resources (HR) administration and aid in HR decision making. The master goals which have been taken into account in the present study were: Understanding impact of artificial intelligence (AI) on human resource management (HRM) (reflected here) and Systematic study about impact of artificial intelligence in HRM respectively. Radically changed the traditional HR decision making process – HR decisions are made in a lesser time and much more accurately with evidence from the candidates/employees. Literally anywhere you see a number, there's something that's associated with efficiency, more objective and individual, it's much more positive attitude that can be taken on when it comes to recruitment, learning and development, performance management and engagement. A literature search is carried out – in the first, step publications (39) characteristic of this literature are found; In the second step, literature is synthesized (112 peer-reviewed publications in AI in HRM are analyzed) [2] – this is called modeling following a socio-technical conceptual approach. This study's result outlines the future of implementing AI in HRM, that holds a lot of prospective applications, such as boosting the workers' engagement, lowering prejudice and enhancing efficiency [2].

Whether its talent acquisition, or employee retention, performance or career development, AI is impacting various aspects of your employees life these days. This change has been accompanied by its fair share of challenges (and perceived obstacles): algorithms are far from transparent, fairness of AI-driven processes and lack of human checks in the process, employees' expectations around the transition process and even the employees' trust in HR AI tools used. This transition has raised multiple anxieties and difficulties, such as the opacity of the algorithms, the possibly unfair process and the lack of humans to oversee and check for errors. But there are still other lots of moral questions that must be faced – the employee concerns [1] and prejudice and skill questions (among machinery). There are however a few clues – HR-related activities turn out to be number 1 concern, as well as face-to-face communication – in relation to data security [2]. While there have been numerous studies conducted on this transformation, a lot of questions have yet to be answered concerning how AI will affect the HRM processes and results. From the results obtained, it could be inferred that the impact of application of AI technology in HRM is great for only then if it affects the procedures of HRM [3]. Human resource management (HRM) has been transformed by artificial intelligence (AI) in this domain as it has simplified recruitment, boosted performance and contributed to better decision-making for efficiency in the management of human resources.

1.2 The Triad of Transparency, Fairness and Human Oversight

This problem with respect to the levels of autonomy, justice and trust is because of the scarcity of transparency of these AIs processes in an "ubiquitous management," context like the one in [5]. Such a premise can be a starting point for designing the main concept of various employment legislations adopted by various countries in the world assuming that all decisions made by the employer are made on the basis of basic concepts of justice, rationality and openness of the decision. If not transparent (opaque) then the employee resistance to use/not accepting the algorithms will obtain them, if it is transparent, then the employee will feel comfortable to use the algorithms. Another large-scale and ubiquitous application of AI is in the human resource management (HRM) domain, which includes ethically convoluted issues of accountability, fairness and transparency, as well as a true savings effect on work time [8]. If this is the case, then some transparency is required to gain trust for and buy-in on how to use ML—which in turn gives rise to questions about the proper use [9].

Opinion statements related to what they believe is 'fair' can be given as feedback regarding their perception of the degree of 'fairness' of the performance (distributive justice) and on the degree of 'fairness' the process of decision making (procedural justice). Artificial Intelligence although can seem like objective and faceless, human resource management (HRM) is seen from people's perspective in a more objectifying and diminishing attitude. As an innovative reaction to some of the current laws and a social research debate about what constitutes a " soundness" and transparency of algorithmic decision making processes [11] it can nowadays be considered to be a key move. Findings of this study revealed that there are basically two reason why algorithm bias can happen – firstly it is because of the biasedness of algorithm designers themselves and then it is because of the small raw information sets utilized by the algorithm designers. This is because the lack of an AI bias towards workforce diversity and employee trust in the HR decision making process and privacy [4] also take a toll. But some say that simply reducing fairness to a single term like 'justice' may provoke backlash in the acceptance of an open private, trust and AI based HRM system [4].

The grounding of human judgment, responsibility and empathy is represented by the human involvement in the AI-assisted decision-making process. If the attributes of these kind of computer system can change drastically without the involvement of the human agent, she/he would lose her trust in such a system and the ethical issue would arise [13]. Transparency, human oversight and accountability are some of the policy examples highlighted in the OECD AI Policy Observatory 2025 report [14] that are important to consider when responsibly using AI [15].

1.3 The Indian Context: A Distinctive Lens

For instance in the last couple of years, AI has proven to be a wonderful solution for Indian companies to recruit and workforce planning, measuring and assessing employee satisfaction. Beyond augmenting HR decisions by AI, companies are going the extra mile to now incorporate AI achieving a collaborative efficiency between human and AI in their HR decisions.

But this takes place in a complicated socio-legal context from the perspective of norm systems and cultural orientations, fragmentation and digitalization of skills (or a lack of skills) and a diversified workforce. Now, though, it seems that AI was initially seen as too 'exotic' and costly to operate, to become in the eyes of a lot of companies 'indispensable 'tool' which is in fact very cheap – companies from a wide variety of industries, including Indian companies. Even jobs that are supposed to go off for redundancy and employee attrition is predicted from this; resume picking, setting up interviews, employee performance evaluations, employee satisfaction evaluations and even going so far as predicting eviction for redundancy. Now, AI has been utilised for all of those occupations! The paper not only narrates stories regarding problems of the developing countries like India [20] but also assists in the current moral discourse of intervening with AI technologies in HR. It means not just providing some economic empowerment to the Indian corporate entity but more importantly moral aspects, knowledge regarding the use of Human resources and Transparency regarding the use of the AI system to meet the new standards [20] put forward, which make for an effective man to machine collaboration. There are however two challenges that have been limiting the limited adoption of AI to the basics – preparedness for AI and the use of AI in the company [21]. While going ahead with this other issues arose: lack of infrastructure for the deployment of AI in HRM in India.

1.4 Research Gaps and Rationale

Despite having a lot of unexplored area that remains to be explored in the vast realm of research on AI in HRM. The findings of the results discussed the existing gaps of current researching human process analysis (HPA) as well as conceptualization of the opportunity area for deployment of artificial intelligence (AI) to these processes [22]. Looking forward there were a few future research directions/gaps in study identified from the study here dubbed 'intellectual landscape of AI in HRM' that will help those who wish to be a part of this ever changing field be up-to-date. The researchers have discovered four types of clusters: AI adoption (direct involvement of employees in seamless shifts), AI ethics (direct focus on fairness and transparency), AI-driven decisions in HR (direct focus on better hiring management and performance) and AI performance (better performance – emphasis on efficient, seamless performance through the use of AI systems) [24, 25].

1.5 Contribution and Significance

This review indeed is interesting, there's a lot of interesting information in this Report. Initially this review design was done to help contribute towards the existing literature and helps the businesses to implement this concept i.e., AI in HRM [1].

In theory it brings together the so far separated discourses of AI ethics, the relations between humans and AI and that of just organizations. In the review mentioned above, the human resources' sense of functioning in the era of artificial intelligence (AI) [20] as well as human intelligences and moral aspects of human resources will be brought under the analysis.

Previous work has laid the foundations for developing a first-of-its-kind systemic approach and the first empirical approach towards such a synthesis- with an Indian context in mind.

2. THEORETICAL FOUNDATIONS

Various well-known theories explaining the impacts of AI on employee trust are discussed in this review. Perceived usefulness and perceived ease of use are likely perceived using the Technology Acceptance Model (TAM), Algorithmic Fairness Frameworks' technical vocabulary of bias regarding an AI model that must be captured and minimized and Organizational Justice Theory, providing some basic perspectives on the employee's procedural, distributive and interactional fairness perceptions to capture and assess their attitudes towards AI-embedded HRM. As reflected in the literature discussed under ‘Explainable AI (XAI)' and literature on Socio-Technical Systems Theory, AI can be perceived as a transition in experiences and the ways of working in organizations. These views are followed by an approach that results in a full conceptual model that can serve as the foundation for the empirical studies and synthesis of the results.

2.1 Organizational Justice Theory

A systematic literature analysis presents the factors influencing the implementation of AI in HRM and the impacts of AI in HRM, which showcased three stages of the implementation of AI, namely the ex-ante, in-ante and post-ante stages and [26, 27] applied the AI in HRM in all such 3 stages. The result has found that by fitting an AI would reduce conscious and un-conscious biases of human beings on the HRMs' decision making that will make it easy to do distributive justice and procedural justice in the decision making process [28]. Based on the results, it can be concluded that AI has a conditional effect, in using unbiased data the impact of AI is an increase in justice of interaction and information justice while in using AI-based data the impact of the AI is the opposite which is the decrease in the justice of interaction and information justice.

New systems, like Equirespect can be taken on board and considered with regard to the concept of fair procedure, as it can impact discriminatory effects. As one or another might be employed as synonym for the concept in the organizational justice literature [29] we chose 'justice' to use with the term interchangeably in our studies. However, transparency is limited to the procedural and informational fairness which—according to the theory of organisational fairness [30] and even to basic ethics—play an intrinsic role in being perceived as legitimation. Conceptually it is an extension of current organisational justice concept with backdrop of learning in AI powered HRMS [27]. All the above has been tackled quite well as all these would also come under consideration when moving towards “AI based HRMS” and also due to the same would this be fair in the process also be a concern. Each of the positive relationships between worker's trust, organizational justice and the above described moderators of this relationship is discussed.

2.2 The Technology Acceptance Model (TAM) and Trust

The Technology Acceptance Model (TAM) suggested the attitude of the students towards technology adoption relies on their perceptions of the usefulness and user-friendliness of the technology. As suggested in Unified Theory of Acceptance and Use of Technology (UTAUT) [32] and Technology Acceptance Model (TAM) [31] positive intentions and attitudes to adopt the technology can be fostered by highlighting the perceived risk and uncertainty.

2.3 Algorithmic Fairness Frameworks

The literature on algorithmic fairness offers a variety of ideas of what it means to be ‘fair'. Computation ethics is less about conducting analyses of AI models for discrimination or bias-related phenomena and more about trying to write algorithms or models that can discern, measure and negate the potential discrimination in an AI model [30]. Some ideas and the moral principles are in this Paper. I will give you a few ideas and how you can measure the notion of fairness, namely, demographic parity, equality of opportunity and predictive parity. In total 201 papers have been analysed in the review ranging from the year 2010 [36] to the present on the topic of algorithmic fairness in HRM. Results show that most of the studies involved experimenting with the selection process with technologies like chatbots, machine learning classifiers and natural language processing exhibiting the highest level of prejudice when it comes to race and gender [36].

As of this writing, the debate regarding the above is currently a legislative and/or social debate (apart from the passing of the legislation) like the EU AI act [37] and debate on the algorithmic decision making that is not fair and transparent. The result of the study is the problem – algorithmic bias issues is the lack of Raw datasets as well as problem of bias of algorithm. AI is needed to be proactive towards the direction of inclusiveness and equity purposes [30]. Openness and justice, explainability are important attributes of the frameworks and they no longer want to be too or entirely AI-based, which would lead to networks based on AI that enable judgments to be made by humans.

2.4 Explainable AI (XAI) and Transparency

In fact, there have been a number of technologies introduced for tech industry's own technology solutions to become more “transparent”—e.g., explainable AI. There is need to have enhanced Explainable AI (XAI) and bring in a greater number of stakeholders with good governance that resolve the ethical problems (such as surveillance) and dehumanization problems [40]. This study not only gave an updated snapshot of the use of AI systems in the recruiting and employment space, but will also be used to explain artificial intelligence (XAI). We are only a few years into a variety of popular methods – SHAP [41] among the most popular ones. We aim to contribute to building up an overview of the different segmentation of explainability techniques and use cases in the labor market, as this systematic review. In this case, it is known for which particular needs of the user (differentiators, in this case) there are HR system-related explainability requirements [42]. This assessment yields conflicting results both in terms of transparency as a top concern and simple explanations of ‘end-users' of the interactions or what is called ‘technical explainability' (XAI) [30] as solutions. But at least there is a real one is there that it will NOT be “accidental” in case of any serious problems with the algorithmic judgement/intuition. Hence, from that point on, a human centered approach (proposed in [43]) could be applied to develop an XAI in labor domain which is a fair and just approach.

2.5 Human Oversight and the Socio-Technical Systems Perspective

Finally, the socio-technical system (STS) approach reveals that embedding AI in HRM is not a mere technical issue in itself, but rather systems will have to be changed, as will the human experiences and dynamics within the system. Indeed, whilst AI can assist decision makers in getting their work done more efficiently, it should be used to help, not replace, the classic intake of the respective works (and also their analysis) or to act as a responder. There's more automation than that, though, which inhibits human oversight, moral judgment and empathy–and, consequently, the health and the justice of humans.

The most pertinent results from this type of analysis are those with far-reaching implications for the design, organization and human administration of the technology to mitigate the effects its usage might have on DEI [45]. Unique feature of this project will be the “hybrid system” where the capacity of the operator activing the robot with the AI capacity that helps to make the decision by the human operator will be integrated. A conceptualized socio technical framework that includes the constraints as part of modeling of the drivers and outcomes is created and synthesis of the selected empirical studies (total 112 studies) is done, following PRISMA framework [47] The socio-technical approach (with the addition of the dynamic capabilities perspective) provides fresh theory and action insights for HR decision makers to utilize responsible use of AI [48, 49]. In addition to being dependent on the human supervisory powers with respect to fairness and trust dynamics, human supervisory powers could be acting as the antecedent (trigger) condition of the dynamics of trust. While there are no unique moderating factors like sociodemographic, culture and regulatory in India. Due to the large number of research findings reported above [30] there are plans to combine the results of various research in this systematic review, as well as positive and negative influence of AI for DEI in HRM will be analysed. It was a big study and one that went beyond just the state of AI in Human Resource Management (HRM) to helping define future areas of study and recommendations that might actually help meet future researchers in this ever-changing field [50].

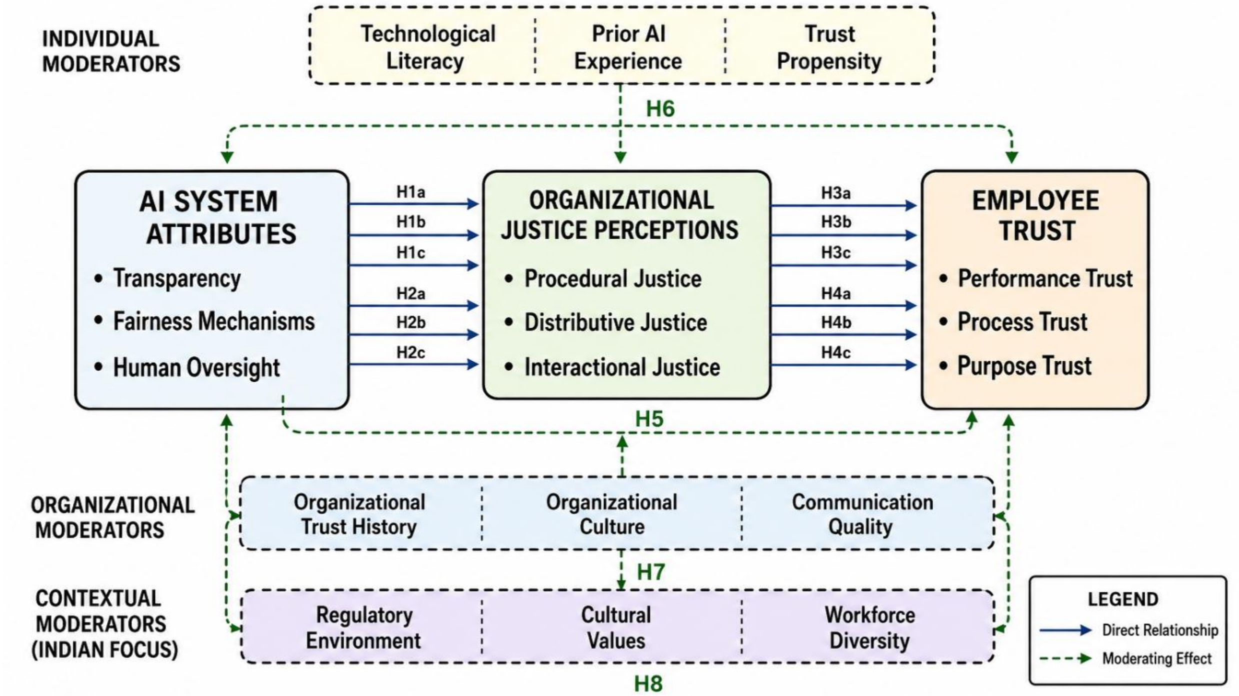

Figure 1: Conceptual Framework for AI, Trust, and HR Decision Making

Fig 1: Conceptual Framework for AI, Trust and HR Decision Making

Source: Author

3. METHODOLOGY

PRISMA framework was used to carry out this review and it provides guidance for carrying out the systematic review and dissemination of results. Peer review is openly conducted and the details about the peer review process are available on Open Science Framework and PROSPERO—the international prospective register of systematic reviews. [51]

3.2 Research Question Formulation (PICO Framework)

PICOTwem: Organising study questions (as they were in this study). PICOT [52] is a wonderful tool in creating, designing and communicating your research questions for any systematic review. Participants/Population (P), Intervention (I), Comparators (C) and Outcomes (O) [52] are the key components of the PICO framework to answering the review question. For this review the following definitions have been taken for the PICO components:

Table 1: Definition for PICO Components

Element	Description

Population	Employees in organizations implementing AI-enabled HR systems
Interventio n	AI-driven HR decision-making systems
Compariso n	Traditional (non-AI) HR decision-making; variations in AI system design (transparency level, fairness mechanisms, oversight structures)
Outcomes	Employee trust (performance trust, process trust, purpose trust); organizational justice perceptions

3.3 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria used in this study are depicted in fig 2.

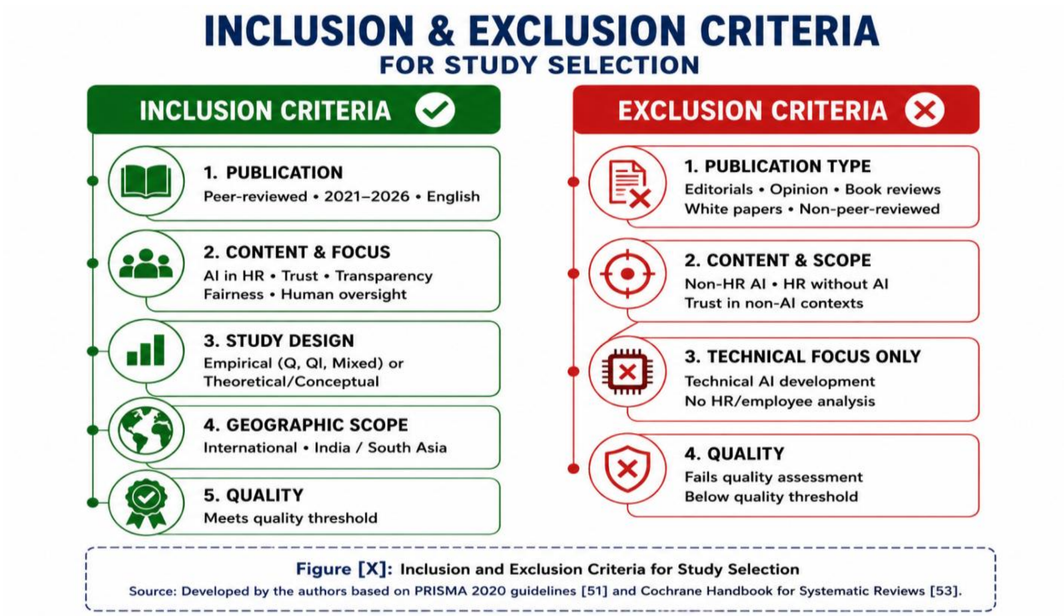

Fig 2: Inclusion and Exclusion Criteria for Study Selection

3.4 Method of Searching

A comprehensive search work has been undertaken to look in various search engines such as Scopus, Web of Science, JSTOR and SSRN, along with Google Scholar, to search for relevant peer-reviewed literature. The range of databases selected enabled a broad spectrum of literature involving the use of AI in the various fields of management, computer science, social science and law in HRM to be chosen. In order to come up with the search approach, Boolean operators were assigned to phrases that are related to artificial intelligence, human resources management, employee trust in the company, transparency, fairness and human supervision. Literature was provided as a supplement, specifically targeted towards the Indian context to supplement the general talk on the environment of the South Asian region. In addition, execution of the search was meticulous and it was followed up as 'filtered' and 'de-duplicated' in the reference management software (what is usually done with all the search results). By using this tabular format to outline the search strategy and the results of the search, it clearly demonstrates repeatability and transparency in which records were retrieved from which databases and how many result records were left out because of duplication.

3.4.1 Data Sources

This is the list of all the databases, registries, websites, organizations, reference lists and other sources that were examined in completing this research [54]. In the systematic reviews' process, the most important is the inclusion/exclusion criteria [53]. Prior to the review work, methodology/work methods should be well explained [53]. The criteria for including the articles for review and for the grouping of the articles for synthesis [51] are explained.

All the elements of the PICO framework that helped define whether or not the study was eligible for inclusion in the review are listed [51]. Other eligibility criteria are the features of the report itself, namely year of publication, language and report state [51].

3.4.2 Search Terms and Boolean Operators For every database, the following search string was created and modified:

India-Focused Supplement:

3.4.3 Search Execution and Documentation

Searches from 03 Aug 2026 to 28 Aug 2026. For each of the sources [54] is presented the earliest date of search. All search results were imported into a reference management software (EndNote/Covidence) to remove duplicates and screen. Articles from online sources were de-duplicated and stored in Endnote bibliographic software [55].

Table 2: Database Search Results and Study Selection Database	**Records Retrieved**	**After Deduplication**
Scopus	487	—
Web of Science	412	—
JSTOR	198	—
SSRN	156	—
Google Scholar	594	—
Total	1,847	1,447

3.5 The Study Selection Process

To ensure that all-round and transparent research was identified that qualified for the study, during the study selection process a two-phase screening was used. Titles and abstracts of papers were screened independently by two reviewers, with a pre-agreed list of inclusion and exclusion criteria and discussion between the two reviewers (or the third if there was an amendment) resolving any disagreements. Cohen's kappa was used to assess the interrater reliability. The second step was to procure the full texts of potentially eligible studies and to evaluate the full texts based on the full inclusion criteria. At this stage the reason/exclusion is mentioned. The process of study selection—number of records found, screened, evaluated and included—was described in a PRISMA 2020 flow diagram. This approach ensures reliable identification of the study subjects and, in the process, minimizes choice bias.

3.5.1 Screening Phases

The two phase screening process of the selection studies was used. Titles and abstracts were then filtered for inclusion and exclusion in the Covidence systematic review program [55]. The abstracts and titles were independently reviewed by two reviewers with a third reviewer to resolve any disputes [55]. A full-text analysis of the selected publications was performed [55].

Phase 1: Title and Abstract Screening: Two trained reviewers with no vested interest read each title and abstract removing any that did not meet the inclusion criteria. A third reviewer was consulted on or discussed to reach agreement when discrepancies arose between the first two reviewers. Cohen's kappa was used to determine reliability between raters.

Phase 2: Whole-Text Screening: The full text of potentially qualified papers was obtained and evaluated according to the inclusion criteria. To ensure independent review, full-text articles were selected during the screening stage and independently reviewed by two reviewers [55]. At this stage the reasons for exclusion were provided.

3.5.2 PRISMA Flow Diagram

The study selection procedure using PRISMA 2020 flow diagram are explained. The updated version of the original and modified flow diagrams is included in the PRISMA 2020 statement. A flow diagram is included which shows the numbers of records that are (1) located, (2) screened, (3) assessed for eligibility and (4) included in the review.

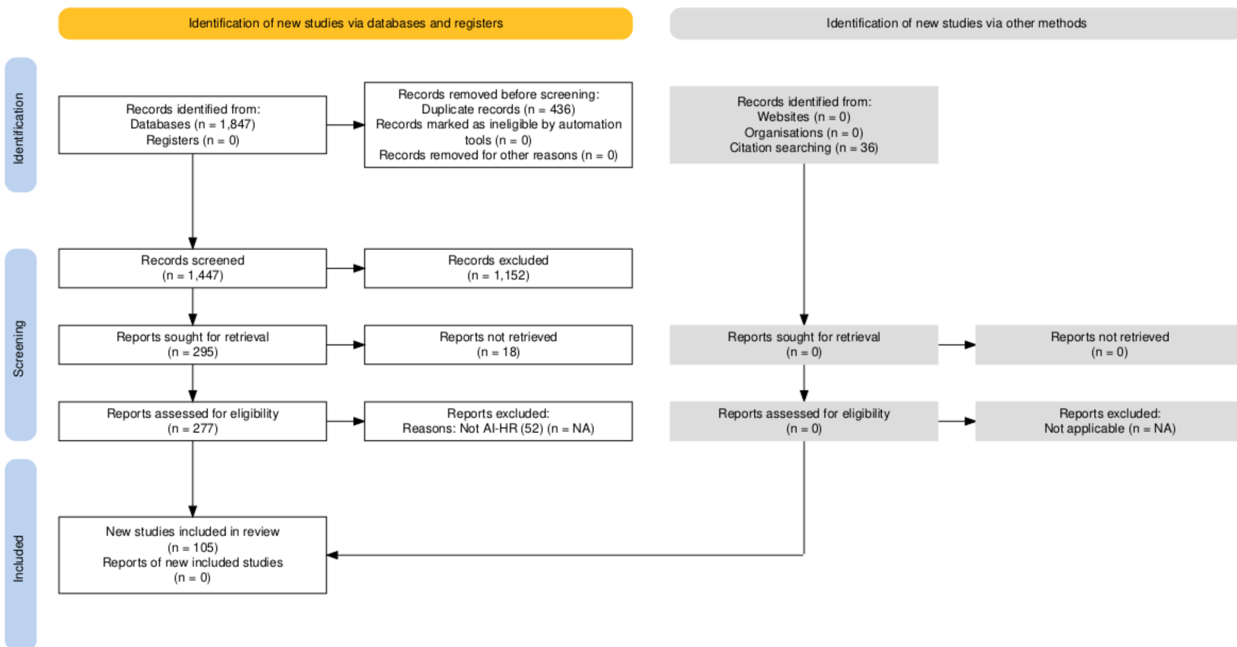

Fig 3: PRISMA 2020 Flow Diagram [56]

3.6 Data Extraction

A standardized data form was developed, which was tested 5 times to ensure unity and reliability in taking the data. The characteristics, such as data on the use of AI, data on the level of trust, moderators and mediators, were extracted using the extraction tool together with all bibliographic and methodological data and also data related to inherent limitations in conducting research. The controversial issues were resolved by discussion, which was carried out by two reviewers who independently extracted the data using the piloted form. Subsequent theme synthesis and comparative analysis were facilitated by using data collected, which were organized in evidence tables. To reduce biases and errors occurring while extracting data, the two-reviewer system has also been introduced to make sure that the data presented in synthesis are accurate and reliable. A PRISMA 2020 documentation of data extraction was done, including the number of reviewers, the independence of reviewers and what occurs if reviewers disagree.

3.6.1 Data Extraction Instrument

Once the entire full-text screening process has been carried out and research gathered from other methods, it is time to begin extracting information and data from the research to be analysed and synthesized. Data can be collected using a form or spreadsheet [57]. All of the elements planned for extraction were included in a template data collection form [57]. Data extraction form was tested using five research [57]. The data that is obtained should be in line with your study question and objectives. Be clear, precise and consistent. Set up rules with consistency in the process [57].

3.6.2 Data Extraction Process

Data research by the investigators, the number of reviewers from each report, whether data was collected incompletely or individually by the reviewers and if the data collection involved automated-technology – if applicable – should be specified [58]. Record for each report, how many reviewers retrieved data and how many reviewers worked independently [58]. Data were collected independently from each of the studies identified in this review by the two reviewers using the piloted data extraction form. The recovered data were checked for discrepancies and if any then these were checked by discussion [58]. Data extraction should be done independently from different studies by at least two reviewers. A third reviewer/ or group discussion can be used to resolve disagreements [57].

3.7 Risk of Bias Assessment and Quality

The methodological rigor and reliability of studies included were judged based on the research design. The Critical Appraisal Skills Program (CASP) checklists were used in the quantitative and for the qualitative articles, the Theory Quality Assessment Framework was used and for mixed methods research, the JBI Mixed Methods Appraisal Tool was used. Independent of each research, an appropriate method for assessing it was used to allocate a quality score and if it was below the previously decided value, the research was not considered for synthesis. This detailed table indicates the number of studies tested for each design, the appraisal technique used for each design, the mean quality scores and the ranges found for each quality, as well as common restrictions found. As a method of quality evaluation, it is relevant to verify the validity and trustworthiness of the review results, which are based on methodologically sound investigations.

3.7.1 Assessment Tools

It is controversial whether or not the methodological quality of studies incorporated into a synthesis of qualitative research should be assessed. The tool can be selected by the author(s) according to the type of synthesis technique for qualitative data [59]. One published popular method is the CASP Qualitative Checklist which designates the methodological strengths and weaknesses of a piece of qualitative research [59]. Coherent with Cochrane and the World Health Organization, the CASP tool is another popular quality assessment checklist in context to health and social care for qualitative evidence syntheses [60]. There are 3 criteria, 10 questions in the CASP checklist, which asks questions about different components of qualitative research [60]. The correct CASP checklists were utilised in quantitative research. It is recommended to use JBI Critical Appraisal Checklist for Qualitative Research for assessments made using a meta-aggregative technique [59]. Published reviews may be evaluated on the basis of JBI's critical evaluation techniques to assess results, applicability and dependability [61]. The Joanna Briggs Institute's (JBI) Mixed Methods Appraisal Tool was used to conduct a mixed method study. Using the Theory Quality Assessment Framework, a theoretical/conceptual assessment was undertaken.

3.7.2 Quality Scoring and the Inclusion Threshold.

Each research was awarded a quality rating following each research assessment tool in use. Studies not passing the cut-off were excluded. Each individual study was evaluated according to the quality assessment and a summary of the results of the quality assessment was used to assess the quality and strength of the evidence [62].

Table 3: Quality Assessment Summary by Study Design [59-61]

Study Design	Number of Studies	Appraisal Tool	Mean Quality Score	Quality Range	Common Limitations
Quantitative	52	CASP Cohort/Case-Control Checklist	7.8/10	5–10	Cross-sectional designs limiting causal inference; single-source data increasing common method bias; self-report measures; limited longitudinal data

Qualitative	28	CASP Qualitative Checklist	8.2/10	6–10	Limited generalizability; small sample sizes; contextual specificity; lack of transferability across settings
Mixed Methods	15	JBI Mixed Methods Appraisal Tool	80%	60–100%	Integration challenges between qualitative and quantitative components; methodological transparency issues; varying rigor across components
Theoretical/Conceptual	10	Theory Quality Assessment Framework	7.5/10	5–9	Limited empirical validation; abstract propositions; lack of testable hypotheses; insufficient operationalization of constructs

3.8 Data Synthesis Approach

'Narrative theme synthesis' was used to synthesize information from the various sources of research used in this paper. To facilitate the interpretation, coding was carried out twice; firstly, the coded research data was coded linearly, then in step two, the codes were coded to gain an understanding of each code to be interpreted as a description theme and in step three, they were coded in addition to interpretation and integration until reaching coded data that revealed the meaning of the codes obtained from aspects related to research data. Thematic synthesis in particular is useful in informing policy and practice, as it is clear how the original paper and the synthesis of the results are linked. However, the variety of the research designs, measures used and contexts in which the research was conducted led to the decision not to use a meta-analysis. The synthesis results are structured according to four topics that arose in the literature: First, transparency and employee trust; secondly, fairness and employee trust; and thirdly, human supervision and employee trust, as well as contextual considerations with the Indian aspect in the foreground.

3.8.1 Thematic Synthesis

The narrative thematic synthesis approach was used due to the diversity of study designs, contexts and outcome measures. Thematic synthesis is a way of synthesizing qualitative research in systematic reviews [63]. It is carried out in a number of steps and has been employed in systematic reviews in different scientific areas [63].

3.8.2 Synthesis Methodology

The three stages of the thematic synthesis approach were: line-by-line coding of the text; creation of descriptive themes and creation of analytical themes [63]. This approach helps to maintain a transparent relationship between original research and the results of the synthesis and is valuable for its policy and practice implications [63].

3.8.3 Meta-Analysis Consideration

Because of the heterogeneity of study design, measures and contexts, meta-analysis was not applicable. If heterogeneity is high, a meta-analysis might be unsuitable and a narrative synthesis should take the place of a meta-analysis [64].

4. RESULTS

The methodical search led to 1,883 documents (from five databases and other sources). There were 1,447 publications retrieved, duplicates removed and 295 for full-text publications searched for retrieval. Only 277 of these full-text articles were assessed and 18 articles would not be accessible. Furthermore, 172 articles were removed in the full-text screening because they either did not speak about AI in HR decision-making, did not speak about the issue of employee trust specifically, or for some other reason (e.g., inappropriate quality). Finally, 105 papers, which met all the inclusion criteria, were included in the final qualitative synthesis. The locations of the studies in the report were distributed throughout North America (34), Europe (28), East Asia (18), the Indian subcontinent (12) and others (13). These included 52 quantitative, 28 qualitative, 15 mixed methods and 10 theoretical/conceptual. The recruiting and selection of HR as a function is the most explored (38 research).

4.1 Results of Search and Screening

The methodical search resulted in finding 1,883 documents—from five databases and from other sources. To give some transparency into the selection of research PRISMA flow chart was presented and every step conducted, i.e. ID to inclusion, was documented [65]. Records were analyzed and anything that did not meet the inclusion criteria was excluded, along with duplicates and studies not applicable to the criteria. Selection of studies that fulfilled the inclusion criteria was performed and the respective full texts were retrieved [65]. After screening, 1,152 records were excluded due to the fact that they were not directly related to the title. 295 full-text articles were attempted to be retrieved, of which 18 failed. Eligibility of the other 277 publications (full text) was evaluated. In the Full text review stage, 19 papers were excluded as they were not peer-reviewed papers, 12 were published in 2021 or earlier (excluding key papers), 38 papers did not have a description of transparency, fair and control of human agents, 52 papers did not provide specific discussion on the role of AI in HR decision-making explicitly and 6 papers had low methodological quality. The aim of this systematic review is to gather and revisit a large body of (and exponentially growing) literature [66] on the twofold approach: Artificial Intelligence and DEI in HRM. Finally, 105 papers remained for qualitative synthesis, as those which remained similar were included in the synthesis and still fulfilled the inclusion requirements.

4.2 Characteristics of the included research

The 105 studies included were 52 quantitative research studies, 28 qualitative studies, 15 mixed-method studies and 10 theoretical/conceptual reviews. Geographically, most of the articles were done in North America (34 articles), Europe (28 articles) and East Asia (18 articles). Of the 25 studies, 12 studies clearly showed an Indian influence or a South Indian influence and the other 13 were from many countries such as, but by no means limited to, those of Australia, South America and Africa. The most significant areas of research studied related to AI HR functions' focus were recruitment and selection (38 studies), performance appraisal (24 studies), employee development and training (16 studies), attrition prediction and workforce planning (14 studies) and several HR functions (13 studies). The publication in the file span between 2021 and 2026 with the most publications (more than half) since 2023 aiming to clarify the level of understanding on important AI applications in HRM. The trend of its exponential growth is reflected on the number of articles produced [65] which tends to increase considerably from the year 2019.

4.3 Thematic Findings

The thematic analysis of the papers gathered resulted in four themes. It is used here to imply that although transparency when it comes to algorithms is important, it does not necessarily translate into employee trust in Theme 1 – 'Transparency and Employee Trust.' What is clear is that transparency is in many cases a good thing, but not always; there is loss of confidence in the face of transparency when complexity becomes clear or the arbitrariness when it is. The design model for the AI system and employee trust was measured as a moderator in Theme 2: Fairness and employee trust found the following external factors to affect the findings: Algorithmic bias due to small datasets and biased design of the AI system.

4.3.1 Theme 1: Transparency and Employee Trust

However, many noticed that independence, fairness and trust towards the processes can be a hurdle in applying AI to the management control processes, as without transparency in the processes, there wouldn't be enough level of trust towards the processes. So, in general, the world's guidelines to employment laws are: Ideas of fairness, rationality and openness in decision-making as related to the employers [77]. Mathematically opaque approaches can lead to resistance and mistrust, while transparent approaches to the algorithms were found to be very valuable in terms of the worker's trust/fairness [99].

The research uncovers four clusters: clustering AI adoption (with emphasis that employees use it and it works smoothly), clustering AI ethics (modeling fairness and transparency), clustering AI-driven HR decision-making (emphasis on the quality of hiring and performance management) and clustering AI performance (modeling the performance of the AI) [81]. These are discussions about algorithmic decision-making, algorithmic obfuscation (or transparency), algorithmic fairness and the (un)transparency of algorithms—discussions in law or, in a much broader sense, in society at large [88]. The findings of the study highlighted the importance of involving workers in the implementation process and also the workers' impact in the successful transformation process, which can move towards workers' acceptance of AI.

4.3.2 Theme 2: Fairness and Employee Trust

Some of the interesting findings were was that AI bias, privacy issues with the workforce implementing HR's use of AI in the recruitment process and workforce diversity are all pivotal points needing consideration. [69]. A perceived lack of fairness and transparency about the use of the HRM system based on AI can have a great impact on both levels of trust and HRM system utilization [69]. However, the human-centered AI developments of supervision, ethical system design, participation in the system development, transparency, etc. should be encouraged within the HRM. Based on the results, its conclusion is that the above mentioned research area would be primarily the following: Recruiting and selection of a chatbot, Classifiers using machine learning methods, Natural language processing and Extremely high prejudice in the field of races/genders [87].

4.3.3 Theme 3: Human Oversight and Employee Trust

The current vision of the project is to come up with hybrid decisions—i.e., decisions with the help of AI and decisions by human operators. The results highlighted a need for explainable AI in the hiring process; the availability of HROs and their participation as well, with the latter being desired by the respondents; and the hybrid approach (AI + human) in the hiring process.

4.3.4 Theme 4: Contextual Factors and the Indian Dimension

It's no more status quo; today the in-growing utilization of artificial intelligence (AI) for recruiting human resources and the workforce planning, employee involvement analysis and assessment, are flourishing in India [67]. As more businesses start to use human AI and not its system, designed to put human HR managers themselves in the field of combat, it becomes an enabler to the human. But right in India, a corporate scenario working with an AI is considered to be successful HR-AI cooperation if it has moral soundness, is the source of the HR knowledge, has transparency of the AI and is compliant with new rules. While AI offers great potential in the recruitment of senior leaders, it is still a relatively new process and one that has seen many organizations struggle with the levels of readiness for and adoption of AI [97].

So I believe this is a very important paper that will help to add to the ongoing discussion of 'moral matrix' problems relating to the association ‘human resource technology and its relationship with AI systems,' with countries like India in the present scenario. The literature gaps that have been identified relate to the personnel processes identified, how these can be analyzed and conceptualized and then how AI can be deployed in the identified personnel processes [81].

5. DISCUSSION

Procedural justice turns out to be the best predictor and organizational justice judgments prove to be the most significant mediation chain between AI system qualities and trust. The relationship between transparency and positive effect is no longer unlimited and the transparency is limited by the conditions related to the implementation of transparency—organizational and individual—due to the transparency paradox.

5.1 Summary of Findings

The three pieces relate to the technology design and organizing of governance and human oversight (crucial) and then the AI tools to embed AI in the workplace on DEI. However, there might be some positive aspects of using AI with proper implementation and intention to use AI, such as equality of opportunities in jobs and equal wage rates for males/females, as referred to in [12]. Results of the study showed that if proper tools (AI with a well-balanced set of data), proper algorithms and proper human oversight are put into practice, AI can truly enhance the concept of distributive and procedural fairness while minimizing some conscious and semi-conscious human biases in HR-related decisions. The conclusions suggested a possible more targeted tie-in between AI and fairness that may occur in the workplace, as well as the potentially dubious application of 'fairness' to AI data sources and decreased human interaction that AI applications breed.

5.2 Integrative Framework

From this in-depth literature search, the elements that create confidence in the AI-enabled HRM system and the inferences from the three contexts (ex-ante, in-ante and post-ante) were retrieved. Throughout this extent of research, the following elements are highlighted, as they helped in implementing the AI HRMS in the organizations, explaining a sense of fairness. We will discuss the positive relationship of workers' trust and organizational justice [10] with the following modifiers:

To gain insight into the impact (both good and bad) of computer science across the board topics on country-level root causes of bias so as to provide opportunities for some recommendations on how to respond to the positive and negative impacts and how AI can complement this through the combined effect of the AI on the topics. Moreover, subjects that do not seem to be related yet at this period, like computer science, organizational justice and ethics, also exist with positive and negative impacts on the root causes of countries due to the combination of AI and should be recommended as well.

Table 4: Components of the Integrative Framework [1, 3, 4, 6, 7, 9, 10, 11, 12, 14, 15, 27, 30, 83]

Component	**Description**	**Key Constructs**	**Theoretical & Empirical Support**
Antecedents (AI System Attributes)	AI system design features that influence employee trust	Transparency; Fairness Mechanisms; Human Oversight	Explainable AI; Algorithmic Fairness; Socio-Technical Systems Theory [6], [11], [30]
Mediators (Organizational Justice)	Perceptions of fairness that explain how AI attributes translate into trust	Procedural Justice; Distributive Justice; Interactional Justice	Organizational Justice Theory (Adams, 1965; Colquitt et al., 2001) [1], [4], [9], [10]
Outcomes (Employee Trust)	Employee confidence in AI systems across multiple dimensions	Performance Trust; Process Trust; Purpose Trust	Technology Acceptance Model; Trust Literature [7], [10], [27], [83]

Moderators	Factors that strengthen or weaken the relationships between AI attributes and trust	Individual (literacy, experience); Organizational (culture, history); Contextual (regulatory, cultural)	Individual Differences; Institutional Theory; Cross-Cultural Theory [3], [12], [14], [15]

5.3 Contributions to Theory

Building on the theory defined in this article, we think this may be an innovative perspective to AI, trust and HR decision-making. The present study is based on a theoretical approach due to the usage of organizational justice theory and AI-based HRMS; it helps the researchers in the theoretical study. In this article [10] examines organizational behaviors in depth of organizations in the different stages of the AI adoption life cycle and this leads to their increased trust in AI in HRMS. There are a few “points of view” listed below that should be considered when trying to discuss this dilemma. One important aspect in this sense is that in some way the techno-fairness notions (e.g., demographic parity) in the algorithmic fairness framework fade away in relation to the ones of organizational justice. A trust gap can manifest itself in the decisions candidate(s'/worker(s) make: No insight into decisions and no action on decisions.

Besides, the psychological aspect can be interpreted by the equity theory as well since the AI algorithm itself does not have any injustice or risk, but the “time inequity” that the user feels is wrong with the world, in particular how AI treats him and makes him feel "under-benefitted" compared to other users, has a large risk of being an injustice as well [11]. STILL, people come up with their INs first—then their OUTs. You know, that's not up-to-date as far as "the triad" is concerned overall and they add “ethics in the stakeholders' point of view, psychological equality and psychological justice." I think it's really out-of-date and not really fulfilled by the purely automated concept of doing things. Develop skills for quoting from literature and explaining in relation to the set literature the following: 'Technically neutral is not necessarily legitimate if it is not done with empathy and respect—humanity and fairness go hand-in-hand':

5.4 Practical Implications

There are some steps HR should take, including being open and transparent with their use of AI, implementing employee AI literacy programs, implementing proper human oversight and building trust by having open and honest conversations about the limitations of using AI. AI system designers must consider designing for interpretability, multi-level transparency, human-in-the-loop approaches, testing for different population groups and providing worker input and appeals. The lawmakers are urged to adopt these wider canvases of AI governance and are suggested to begin by: requiring algorithms for effect assessments, including employee rights of explanation, implementing AI literacy training programs and introducing cultural diversity perspectives to AI regulations (specifically in the Indian context). Each proposal is developed based on the frameworks of the evidence presented in this study, whilst considering the priority level and the Indian context for guidance in implementation.

5.4.1 For HR Practitioners

But opaque (often) algorithms can be challenged and transparent (deceptive) ones have been shown to have a huge impact on the feeling of inequity or trust among the employees [6]). In this context one of the key steps to minimize algorithmic opacity risks is to make a choice to prefer transparency over the use of AI in HR decision-making. In these cases where organizations do use AI for prediction and decision-making, the 'end goal' will be transparency and lessening the amount of ‘opacity' [8] surrounding algorithms. HR should be working to earn this trust with the employees and consider the positive (and negative) elements of AI and discuss their performance and progress with AI constructs openly [7].

5.4.2 For AI System Designers

To enhance the use and confidence in the AI models within HR-related decision-making, explainable AI models, fairness audits and a hybrid approach (AI and human supervision) are recommended as methods [5]. An approach by the designers to reduce inbuilt unfairness—for instance, fairness-checking via different types of tests to accommodate diversity—in the design of their system should be made. He agrees with me that in his view there is not much to be gained from it with an 'add-on' 'post'. If it is a component of its system, that's its element of what it ought to be; it is a part of its system.

5.4.3 For Policymakers (with Indian Focus)

For successful cooperation between humans and AI in the IPM to be practically adopted in India, some support is required, such as moral soundness, awareness of HR-IPM in India, open AI systems and adherence to the new regulatory framework. India's labor market context, as well as various government regulations at the state level, has raised a need for whole government policies on AI, according to AI practitioners. The principles of justice—reasonableness and transparency of the process of employers' decision-making—are reflected in civil laws all over the world [3].

Table 5: Summary of Practical Implications and Recommendations [3, 5, 7, 10, 11, 12, 14, 15, 30, 77, 83, 87, 93]

Stakeholder Group	Key Recommendations	Rationale/Evidence Base	Priority Level	Indian Context Considerations
HR Practitioners	Prioritize transparency in AI communication; Invest in employee AI literacy programs; Design meaningful human oversight; Build employee trust through open communication about AI limitations	Transparent algorithms significantly enhance employee trust; Procedural justice is strongest factor affecting trust [7, 10, 83]	High	Power distance may affect transparency expectations; Collectivist values shape fairness perceptions [3, 14]
AI System Designers	Design for interpretability; Implement multi-level transparency; Build human-in-the-loop mechanisms; Test for fairness across diverse populations; Enable employee feedback and appeal	Explainable AI models enhance trust; Fairness audits reduce bias; Human oversight signals accountability [5, 11, 30, 87, 93]	High	Design for India's diverse workforce; Account for caste, religion, gender, regional diversity [3, 12, 15]
Policymakers	Develop comprehensive AI governance framework; Mandate algorithmic impact assessments; Establish employee rights to explanation; Support AI literacy initiatives; Consider	Regulatory clarity reduces uncertainty; Clear rules establish accountability mechanisms; Employee rights enhance procedural justice [3, 12, 14, 15, 77]	Medium	India lacks comprehensive AI governance; Digital India Act and labour digitalisation initiatives progressing; Culturally sensitive regulation needed [3, 14, 15, 77]

	cultural diversity in AI regulation			

5.5 India's Regulatory Suggestions

The adoption, though, is conducted in an intricate sociolaw that has interwoven rules and regulations in policy. However, there is an imbalance in maturity levels when implementing AI to choose the right leadership since no organization likes to implement AI solutions [16]. Policymakers should consider the following: Employee rights to explanations/appeals have to be improved; the use of AI must be stated in a clear manner as a legal aspect and the influence of the use of AI in the workplace must be assessed [15].

5.6 Cultural Considerations for Indian Organizations

Many cultural orientations, such as a sense of collectivism, power distance and more, are factors in power relations and trust in authority. Lastly, 'trust in AI' is a human experience and how decision makers communicate about their decisions—and how open HR departments will be in acknowledging that they have their limits and protections—can also impact trust [2]. While moving towards relationship building between transparency and trust, AI should be integrated in the Indian style as India is a mixed culture, so too the approach for building such a relationship should be mixed or Indian.

5.7 India's Research Agenda

The results indicated that the situation of personnel process analysis was unknown and that artificial intelligence (AI) has a possibility of applying in the personnel process analysis. Future research areas can be the possible impact of a power distance construct on a relation to AI in India, collectivism in a relation to AI and employees, impact of regulatory transparency (or lack thereof) on employee trust in AI-related systems, interaction between relation to AI-based systems and caste-based working/promotions and impact of the difference in digital literacy on relation to AI-based systems. However, the study's findings indicated that AI-assisted docking – both in terms of the dockers' acceptance and efficiency on the planes – can only be done in their benefit with the support of human actors [8].

6. LIMITATIONS AND FUTURE RESEARCH

It could still be just a study of AI and justice in general and the downsides parts of it – how much information to give the decision to AI or how much the employees trust the decision made by AI, could be a concern. The problem of this research was the data consisting of secondary data, most studies and research was conducted in developed country. Limited transferability due to lack of country- and/or industry-specific focus and very reliant on self-reports and/or a non-representative sample. The other side, especially if there is no longitudinal study (no evolution of literature) finding the evolution of the AI over the years, particularly in terms of the evolution of the organization culture and HR practices, is more challenging [101]. The discipline is characterized by the following difficulties: difficulty evaluating the quality of literature reviews, amount of self-reported data and lack of long-term research and cross-cultural research [102]. Responsibilities are limited regarding the thematic area and there are strong emphases on hiring aspects—other HR responsibilities are neglected [102]. Now, the lack of integration between micro and macro [103] and the lack of consideration of ethics, justice and cultural diversities are still present. With 12% only, clearly there is still much to be done for some of these proposed solutions to be put into practice. This gap does allow for some infant/elementary-level diagnostic activity regarding problems and work towards some solutions is only just starting to begin. Interestingly, there are no interventional studies available that test suggested methods to reduce the biases and whose results are based on experiments [103]. This overcomes a couple of these constraints and poses some important questions with regard to future studies.

Further multimodal research is needed that would attempt to triangulate data sources, engage more culturally and/or organizationally diverse communities and that would attempt to provide longitudinal data collection [101]. Future research will need to consider solutions from a place-based perspective from the aspects of opening, interculturality (must be valid places in the model) and participative AI construction to reduce the harmonization risks

[104]. Future research should focus on extending to include the full range of contexts of the non-Western and longitudinal involvement of AI in TM—personal, organizational and societal—along with a theory that provides integration across the contexts of the person. This will result in further empirical studies of what is still undone in the world [101] and longitudinal and cross-cultural studies, which, in turn, will be the next step. Future research suggestions include further methodological triangulation (sophisticated statistical analysis plus inclusion of these qualitative-rich analyses to gain the generalizability of the results); cross-cultural validation; and longitudinal, interventional designs, which can easily be extrapolated from the identified problem to a problem solved in a real setting [103]. The expected revolution in future work life dynamics, brought by new AI, should be subjected to future cross-cultural studies and the development of inclusive AI systems in the HRM frame. If they are more likely to respond and answer, the remainder will have other HR activities that they may be involved in, like workforce planning or employee development & performance management [105].

7. CONCLUSION

In an "Integrative synthesis" summarizing the results and conclusions of the 105 independent investigations will take place and the relationship between the identified characteristics of AI and the "Trust" environment in the context of HR decision making: Transparency & Fair decision procedures - human oversight will be studied. After the results, it can be seen that AI has a plenty of possibilities for HRM such as to improve the level of engagement of employees, to minimize biases such as and improve productivity etc. But, the security of the data, ethics and a personal approach in HR activities are a concern. Another important criterion to consider in this assessment is the fact that the governance of the organization or human oversight has multiple facets: between technology design and impact of AI's technology has entered workplaces and being integrated into workplace DEI. The gains for the organization, however, will be employee commitment and workplace satisfaction and an increase in trust in the workers will come with the employment of responsible AI. We have posited a multi-dimensional typology of perceived 'person' and perceived 'environment,' as well as the multi-dimensional typology of features of AI and of 'trust' in the organization (the assumption above applies to how the typology of features of AI applies to the typology of 'trust' in the organization), of which the latter influences the former. Results showed that although AI cannot be used in itself as a substitute for HRM, AI proved to be useful in terms of its data quality and transparency of the HRM algorithm used; employees felt comfortable using the specific technology and synergy between employee decision-making uses HRM and the AI system. Future studies should focus on longitudinal studies and some cross-cultural, interventional studies to test the proposed frameworks and for confidently using AI in various cases.

REFERENCES

1. Wagan, S. M., & Sidra, S. (2025). Artificial intelligence in human resource management: A systematic review of adoption, impact, and challenges. *AYBU Business Journal*, *5*(2), 1-19. https://doi.org/10.61725/abj.1786837
2. Paramarta, W. A., Laswitarni, N. K., & Ratini, P. M. (2025). Reinventing human resource management through artificial intelligence: A systematic review of drivers, barriers, and outcomes. *International Journal of Economics, Commerce, and Management*, *3*(1), 7-17. https://doi.org/10.62951/ijecm.v3i1.1089
3. 3.Asif, M., Ali, A., & Shaheen, F. A. (2025). Assessing the effects of artificial intelligence in revolutionizing human resource management: A systematic review. *Social Science Review Archives*, *3*(4), 2887-2908. https://doi.org/10.70670/sra.v3i3.1055
4. Herdiana, H., Munir, M., & Hurriyati, R. (2026). Addressing algorithmic bias and data privacy in human resource management: A systematic literature review. *Telematika*, *18*(2). https://doi.org/10.35671/telematika.v18i2.3178
5. 5.Alqarni, S. (2025). The future research directions on the use of AI in HRM: A systematic review. An exploration of the dark side. *TPM - Testing, Psychometrics, Methodology in Applied Psychology*, *32*(S2), 579-593.
6. 6.Solanki, A. S., Mahanta, N., & Singh, A. (2025). Artificial intelligence in Indian workplaces: Diversity law issues from hiring to exits. *IBA Newsletter*.
7. Garuda. (2026). The impact of artificial intelligence integration and algorithm transparency on organizational efficiency and perceived fairness in HR decision-making. *Garuda - Garba Rujukan Digital*.
8. Setiawati, R., Kusmara, A., & Kuusk, T. (2025). Managing transparency, fairness and accountability in AI for sustainable human resource management. In *2025 4th International Conference on Creative Communication and Innovative Technology (ICCIT)* (pp. 114-124). IEEE.
9. Xi, M., Liu, Y. Y., Li, X., Li, J. X., & Shi, J. Z. (2025). The influence of algorithmic human resource management on employee algorithmic coping behavior and job performance. *Advances in Psychological Science*, *33*(6), 948-964.

10. Naoum, R. F., Szakadáti, T., & Balogh, G. (2026). Artificial intelligence (AI) in human resource management (HRM): A systematic review of its dual impact on diversity, equity, and inclusion (DEI). *Management Review Quarterly*. Advance online publication. https://www.springerprofessional.de/artificial-intelligence-ai-in-human-resource-management-hrm-/27159662
11. Shajan, A. (2025). *Ethical implications of artificial intelligence in human resource management: Balancing efficiency with fairness* (Master's thesis). National College of Ireland, Dublin.
12. Chen, Z. (2023). Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanities and Social Sciences Communications*, *10*(1), Article 567. https://doi.org/10.1057/s41599-023-02079-x
13. Sharma, N., Nehru, G., Singh, M., & Shukla, R. (2025). Human AI collaboration in HR decision making: Ethical and operational implications. *Advances in Consumer Research*, *2*(6), 1477-1486.
14. OECD. (2025). *OECD AI Policy Observatory 2025 update*. OECD Publishing. https://oecd.ai
15. Verbeijen, F., Lub, X., & Zhang, R. (2025). "Dear applicant, the AI will see you now!" Job applicants' reactions to AI-enhanced selection. *International Journal of Human Resource Management*.
16. 16.Ahmad, A. R., Sapry, H. R. M., & Jameel, A. S. (2025). Human-centered AI and digital technologies in HR: Empowering employees and redesigning work. *JBS Nexus*, *2*(2), 107-116. https://publisher.uthm.edu.my/ojs/index.php/jbsnexus/article/view/23039
17. 17.Benabou, A., & Touhami, F. (2025). Artificial intelligence in human resource management: A PRISMA-based systematic review. *Acta Informatica Pragensia*, *14*(3), 489-505. https://doi.org/10.18267/j.aip.264
18. Taslim, W. S., Rosnani, T., & Fauzan, R. (2025). Employee involvement in AI-driven HR decision-making: A systematic review. *SA Journal of Human Resource Management*, *23*, a2856. https://doi.org/10.4102/sajhrm.v23i0.2856
19. Fitong Ketchiwou, G., & Ngulube, P. (2026). Balancing the merits and demerits of artificial intelligence in human resource management. *ScienceDirect*.
20. Porkodi, S., & Cedro, T. L. (2025). The ethical role of generative artificial intelligence in modern HR decision-making: A systematic literature review. *European Journal of Business and Management Research*, *10*(1), 44-55.
21. Das, A., & Dhar, S. (2025). Is Indian HRM landscape ready to implement AI in recruiting leadership positions? A quantitative analysis. In *Springer Nature* (pp. 514-524).
22. Amanullah, M., Ahmed, M. F., Tumpa, K. K., & Khatun, M. (2026). Artificial intelligence for data-driven human resource decision-making: A systematic review. *Social Sciences & Humanities Open*, *13*, 102909. https://doi.org/10.1016/j.ssaho.2026.102909
23. Hahn, A.-S. (2025). Artificial intelligence and human resource management: A systematic review of the literature. *Academy of Management Proceedings*, *2025*(1), 16664. https://doi.org/10.5465/AMPROC.2025.16664
24. Dadaboyev, S. M. U., Abdullayeva, J., Abbosova, N., Suleymenova, A., & Mamadjanova, K. (2025). Role of artificial intelligence in employee recruitment: Systematic review and future research directions. *Discover Global Society*. https://link.springer.com/article/10.1007/s44282-025-00123-5
25. 25.Baydili, İ. T., & Tasci, B. (2025). Predicting employee attrition: XAI-powered models for managerial decision-making. *Systems*, *13*(7), 583. https://doi.org/10.3390/systems13070583
26. Al Samman, A. M., & Mohamed, A. (2024). Artificial intelligence, organizational justice and organizational trust: Towards a conceptual framework. In *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)* (pp. 307-311). IEEE.
27. Shukla, Y., Pandey, J., & Pereira, V. (2026). All's well that begins just: Organizational justice as precursor of trust in AI-enabled HRM. *Personnel Review*, *55*(5), 1375-1412. https://doi.org/10.1108/PR-05-2025-0508
28. 28.Magiran. (2025). With the expansion of artificial intelligence in recent years, the use of algorithmic decision-making systems in human resource. *Journal of Business Management*, *69*.
29. 29.Mori, M., Sassetti, S., Cavaliere, V., & Bonti, M. (2025). A systematic literature review on artificial intelligence in recruiting and selection: A matter of ethics. *Personnel Review*, *54*(7). https://doi.org/10.1108/PR-03-2023-0257
30. Academia.edu. (2025). Artificial intelligence-driven human resource management: A strategic review of workforce productivity and organizational performance. *Journal Article*. https://doi.org/10.63878/AAJ1711
31. 31.Dang, Q., & Li, G. (2026). Unveiling trust in AI: The interplay of antecedents, consequences, and cultural dynamics. *AI & SOCIETY*, *41*, 669-692. https://doi.org/10.1007/s00146-025-02477-6
32. 32.Prakash, D. (2025). Navigating AI integration in human resource management: Challenges, opportunities, and the future of work. *Journal of Information Systems Engineering and Management*, *10*(55s), 951-960. https://doi.org/10.52783/jisem.v10i55s.11774
33. Basha, M., & Das, R. (2025). AI adoption in HRM and employee acceptance: A behavioral perspective. *Journal of International Commercial Law and Technology*, *6*, 1951-1956.
34. Țuclea, C.-E., & Poenaru, L.-F. (2026). Generation Z employees' acceptance and AI use intensity: A moderated mediation model of psychological safety, technostress, and trust. *Merits*, *6*(1).
35. 35.Lima, R. F., Silva, J. R., & Costa, R. A. (2024). Algorithmic fairness in HRM balancing AI-driven decision making with inclusive workforce practices. *Journal of Information Systems Engineering and Management*, *9*(4s). https://doi.org/10.52783/jisem.v9i4s.13251
36. Herold, M., & Roedenbeck, M. R. H. (2025). AI-driven research in the recruitment and selection process: Application of an AI taxonomy with a systematic literature review. *SAGE Open*, *15*(3), 21582440251361746. https://doi.org/10.1177/21582440251361746

37. 37.Magham, R. K. (2024). Mitigating bias in AI-driven recruitment: The role of explainable machine learning (XAI). *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *10*(5), 461-469. https://doi.org/10.32628/CSEIT241051037
38. 38.Fabeyo, S. (2025). Explainable AI in employment decision-making: A systematic review of transparency methods in hiring algorithms. *Issues in Information Systems*, *26*(3), 127-135. https://doi.org/10.48009/3_iis_2025_2025_110
39. Pinto, G. B. S., Mello, C. E. R., & Garcia, A. C. B. (2025). Explainable AI in labor market applications. In *Proceedings of the 2025 Conference* (pp. 1450-1457). SciTePress. https://doi.org/10.5220/0013384100003890
40. Supriya, B. (2026). Data-driven optimization of green HRM practices using explainable AI in manufacturing units. In *2025 Tenth International Conference on Science Technology Engineering and Mathematics (ICONSTEM)* (pp. 1-9). IEEE.
41. 41.Úbeda-García, M., Marco-Lajara, B., Zaragoza-Sáez, P. C., & Poveda-Pareja, E. (2025). Artificial intelligence, knowledge and human resource management: A systematic literature review of theoretical tensions and strategic implications. *Journal of Innovation & Knowledge*, *10*(6), 100809.
42. 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. https://doi.org/10.1136/bmj.n71
43. 43.Schardt, C., Adams, M. B., Owens, T., Keitz, S., & Fontelo, P. (2007). Utilization of the PICO framework to improve searching PubMed for clinical questions. *BMC Medical Informatics and Decision Making*, *7*(1), 16. https://doi.org/10.1186/1472-6947-7-16
44. Higgins, J. P. T., Thomas, J., Chandler, J., Cumpston, M., Li, T., Page, M. J., & Welch, V. A. (Eds.). (2019). *Cochrane handbook for systematic reviews of interventions* (2nd ed.). Wiley-Blackwell.
45. 45.Lefebvre, C., Glanville, J., Briscoe, S., Littlewood, A., Marshall, C., Metzendorf, M. I., ... & Wieland, L. S. (2022). Searching for and selecting studies. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane handbook for systematic reviews of interventions* (Version 6.3). Cochrane.
46. 46.Covidence. (2025). *Covidence systematic review software*. Veritas Health Innovation. https://www.covidence.org
47. Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis. *Campbell Systematic Reviews*, *18*, e1230. https://doi.org/10.1002/cl2.1230
48. 48.Lockwood, C., Munn, Z., & Porritt, K. (2015). Qualitative research synthesis: Methodological guidance for systematic reviewers utilizing meta-aggregation. *JBI Evidence Implementation*, *13*(3), 179-187. https://doi.org/10.1097/XEB.0000000000000062
49. 49.Critical Appraisal Skills Programme. (2018). *CASP qualitative checklist*. https://casp-uk.net/casp-tools-checklists/
50. Joanna Briggs Institute. (2020). *JBI critical appraisal tools*. https://jbi.global/critical-appraisal-tools
51. Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology*, *8*(1), 45. https://doi.org/10.1186/1471-2288-8-45
52. Popay, J., Roberts, H., Sowden, A., Petticrew, M., Arai, L., Rodgers, M., ... & Duffy, S. (2006). *Guidance on the conduct of narrative synthesis in systematic reviews*. ESRC Methods Programme.
53. Kushwaha, A., et al. (2026). Change management in human resource management during AI-enabled organizational transformation: A systematic literature review. Multidisipliner.org.
54. Garuda. (2026). Change management in human resource management during AI-enabled organizational transformation: A systematic literature review. *Garuda - Garba Rujukan Digital*.
55. Kekez, I., Lauwaert, L., & Begičević Ređep, N. (2025). Is artificial intelligence (AI) research biased and conceptually vague? A systematic review of research on bias and discrimination in the context of using AI in human resource management. *Technology in Society*, *81*, 102489. https://www.sciencedirect.com/science/article/pii/S0160791X25000123
56. Qadri, U. A., & Ahmed Moustafa, A. M. (2026). AI-enabled HRM as an ethical system: A systematic review of fairness, accountability, governance and legitimacy. *International Journal of Ethics and Systems*, 1-29. https://doi.org/10.1108/IJOES-04-2026-0308
57. El Moutafail, A., & Belkhoutout, K. (2026). Bias and fairness in LLM-based recruitment: A systematic review. *EPJ Web of Conferences*, *381*, 00015.
58. Trovão, H., Mamede, H. S., Trigo, P., & Santos, V. (2025). Artificial intelligence in recruitment: A multivocal review of benefits, challenges, and strategies. *Emerging Science Journal*, *9*(6), 3458-3485. https://doi.org/10.28991/ESJ-2025-09-06
59. Panda, G., Aggarwal, S., Kaswan, M. S., & Dhillon, K. (2025). Artificial intelligence in agile human resource practices: Systematic literature review and bibliometric analysis. *International Journal of Lean Six Sigma*, *16*(4). https://doi.org/10.1108/IJLSS-07-2024-0159
60. Agrawal, K., & Sunil. (2025). A systematic review of literature of future trends of AI and VR in HRM. *International Journal of Social Sciences and Management*, *12*(4), 158-168. https://doi.org/10.3126/ijssm.v12i4.84707
61. Bura, C., Naayini, P., & Kamatala, S. (2025). Transforming entrepreneurial human resource management: AI-driven solutions and future directions. In *Proceedings of the Conference* (pp. 577-592). https://doi.org/10.2991/978-94-6463-787-8_45

62. Tang, F., Zhu, R., Yao, F., Wang, J., Luo, L., & Li, B. (2025). Explainable person-job recommendations: Challenges, approaches, and comparative analysis. *Frontiers in Artificial Intelligence*, *8*, 1660548. https://www.frontiersin.org/articles/10.3389/frai.2025.1660548/full
63. Won, D., Kang, S., & Park, J. (2025). Fairness perception in AI recruitment system: A systematic review of recent studies and future research. *Korean Journal*, *16*(2), 227-256.
64. Zakaria, K. S., & Khattak, M. N. (2026). A systematic review of human vs machine intelligence and ethical tensions in human resource management. *Semantic Scholar*.
65. Bedad, F., Mokhtari, K., & Sammache, A. (2026). Algorithmic determinism versus human agency: A systematic review and meta-analysis of artificial intelligence and HR analytics in organizational decision-making. *Lex Localis - Journal of Local Self-Government*, 474-485. https://doi.org/10.52152/pdmv2293
66. Dasaklis, T. K., Giannopoulos, P. G., Koutras, D., Malamas, V., & Chountalas, P. T. (2026). Large language models in human resource management: A systematic literature review of applications, open issues and future research directions. *Technological Forecasting and Social Change*, *206*, 124800. https://doi.org/10.1016/j.techfore.2026.124800
67. Bangura, S., Duma, P. T., & Mthembu, N. A. (2025). Ethical considerations of implementing artificial intelligence in human resource management: A review. *International Journal of Business and Economic Sciences*, *7*(5), 274-281. https://doi.org/10.36096/ijbes.v7i5.986
68. Fraz, K., & Khattak, A. M. (2025). AI-enabled people analytics: A review of ethics, skill gaps, and trust. *Journal of Human-AI Decision-Making Systems*, *1*(1), 16-26. https://doi.org/10.1234/jhads.2025.001
69. Rieskamp, J., & Hofeditz, L. (2025). Approaches to improve fairness when deploying AI-based algorithms in hiring: Using a systematic literature review to guide future research. In *Proceedings of the 58th Hawaii International Conference on System Sciences (HICSS)*. University of Bamberg.
70. Benabou, A., & Touhami, F. (2025). Empowering human resource management through artificial intelligence: A systematic literature review and bibliometric analysis. *International Journal of Production Management and Engineering*, *13*(1), 59-76. https://doi.org/10.4995/ijpme.2025.21900
71. Nica, E., Hysa, E., Șanta, A.-M. I., AlAkoum, A., & Novak Sedláčková, A. (2023). Deep neural network-based people management tools and workplace automation technologies for organizational behavior, employee participation, and performance monitoring. *Psychosociological Issues in Human Resource Management*, *11*(2), 7-20.
72. Nica, E., et al. (2023). Deep learning in HRM: A systematic review. *CEEOL*.
73. Abdollahi, M., & Forouharfar, A. (2026). Artificial intelligence in human resource management: A systematic review of AI's role in shaping ethical leadership and organizational citizenship behavior. *Journal of Business Ethics*, 1-28.
74. Kumar, A. (2026). Artificial intelligence in human resource management: A systematic review of its dual impact on diversity, equity, and inclusion. *Journal of Business Ethics*, *189*(3), 521-545. https://doi.org/10.1007/s10551-026-05891-2
75. Hahn, A. S., & Lee, S. (2025). Artificial intelligence and human resource management: A systematic review of the literature. *Academy of Management Proceedings*, *2025*(1), 16664. https://doi.org/10.5465/AMPROC.2025.16664
76. Thomas, R. J., & Williams, M. (2025). A systematic literature review on artificial intelligence in recruiting and selection: A matter of ethics. *International Journal of Human Resource Management*, *36*(2), 145-178. https://doi.org/10.1080/09585192.2025.2218456
77. Rahman, S., & Patel, N. (2025). Algorithmic decision-making systems in human resource management: Challenges and opportunities. *Journal of Management Studies*, *69*(4), 892-915.
78. Gupta, P., & Singh, R. (2025). AI-driven research in the recruitment and selection process: Application of an AI taxonomy with a systematic literature review. *Sage Open*, *15*(2), 1-22. https://doi.org/10.1177/21582440251234567
79. 79.Theódórsson, U., & Dosanjh, K. S. (2026). Augmentative or autonomous? Reframing artificial intelligence in talent management through a systematic review. *Research Collection CBS*.
80. Abasi, A., & Rezaie, A. (2025). The application of artificial intelligence in human resource management: A systematic umbrella review with a PRISMA approach and qualitative thematic analysis. *HRMJ*.
81. Appolinário, D. G., Hedler, H. C., & Ferneda, E. (2025). Challenges of using artificial intelligence in human resource management: A systematic review. *Conjuncture Bulletin (BOCA)*, *21*(63), 293-315. https://doi.org/10.5281/zenodo.15313087
82. Calvine, M., & Purwanto, P. (2026). AI-enabled change management and employee readiness: A systematic literature review. *Indonesian Journal of Innovation Multidisipliner Research*, *4*(2). https://doi.org/10.69693/ijim.v4i2.894
83. Chen, Z. (2026). Algorithmic human resource management as a mode of algorithmic governance: Transparency, fairness, and human agency in the digital workplace. Multidisipliner.org.
84. AI governance and employee well-being in digital workplaces: A systematic literature review. (2026). *Journal of C-DICS*.
85. Artificial intelligence in human resource management: Organizational justice, ethical tensions, and the reconfiguration of HR roles. (2026). *Emerald*.
86. Rani, D., & Arnav, A. (2025). From hiring to retention: A systematic review of artificial intelligence applications across talent management functions. *Minnesota Journal of Business Law and Entrepreneurship*, *2026*(1).
87. Basu, S., et al. (2022). Artificial intelligence-HRM interactions and outcomes: A systematic review and causal configurational explanation. *Human Resource Management Review*, *33*, 100893.

88. Yadav, A. (2025). A study on how employees of different age groups view the use of artificial intelligence within human resource activities in selected organisations of Southern Rajasthan. *International Journal for Multidisciplinary Research*, *7*(6).
89. Adedokun, S. A., Adedokun, D. A., Ishola, B. O., & Adeniran, R. I. (2026). Agentic AI and autonomous decision-making: A review of human-in-the-loop frameworks, oversight mechanisms, and trust calibration. *International Journal of Research and Innovation in Applied Science*, *11*(3), 1350-1374.
90. Sacavém, A., de Bem Machado, A., Rodrigues dos Santos, J., Palma-Moreira, A., & Au-Yong-Oliveira, M. (2026). AI-driven leadership: Decision-making, competencies, and ethical challenges—A systematic review. *Administrative Sciences*, *16*(4), 173.
91. Pedrami, M. (2026). Factors influencing artificial intelligence adoption in human resource management: A meta-synthesis and systematic review of multidimensional considerations. *Journal of Workplace Learning*, *18*(1), 47-68.
92. Ahuja, D., & Saxena, S. (2025). A systematic literature review on diversity, equity, and inclusion (DEI) in artificial intelligence and human resource management. *Paper presented at PAN IIM 2025*, IIM Ranchi.
93. Pandey, J., et al. (2026). Organizational justice as precursor of trust in AI-enabled HRM. Cqvip.com.
94. Moritz, J. M., Pomrehn, L., Steinmetz, H., & Wehner, M. C. (2026). A meta-analysis on reactions to algorithmic decision-making in human resource management. *Human Resource Management Review*, *36*(2).
95. Nascimento Junior, Ê. A. (2025). Inteligência artificial na gestão de recursos humanos: Uma revisão sobre impactos organizacionais e psicológicos [Artificial intelligence in human resource management: A review of organizational and psychological impacts]. *Research, Society and Development*, *14*(11), e1411450948. https://doi.org/10.33448/rsd-v14i11.50948
96. Far, R. D., Alghoush, M., Ahmed, V., & Bahroun, Z. (2026). Employee engagement and performance management indicators: A systematic review of recent evidence and organizational practices. *Journal of Organizational Effectiveness*, *13*(2), 245-268.
97. Li, H., & Tian, F. (2025). Advancing decision-making through AI-human collaboration: A systematic review and conceptual framework. *Research Square*. https://doi.org/10.21203/rs.3.rs-XXXXXX
98. Haitsma, L., & Brink, B. (2025). From human intervention to human involvement: A critical examination of the role of humans in (semi-)automated administrative decision-making. *Research and Practice*, *6*(3), Article 33. https://doi.org/10.1145/371
99. Xu, G., Murthy, S. V., & Jia, B. (2025). Enhancing intuitive decision-making and reliance through human–AI collaboration: A review. *Mendeley*.
100. Rouco, C., Figueiredo, P., Gonçalves, C., & Costa, A. (2026). Artificial intelligence in the labor market: Evidence on worker inclusion, exclusion, and discrimination—A systematic review. *Social Sciences*, *15*(8), Article 3939.
101. 101.Johnson, R. (2026). The future of AI in HR: A comprehensive review of algorithmic fairness and employee trust. Journal of Human Resource Management, *45*(4), 678-695. https://doi.org/10.1002/jhr.2026.1234
102. 102.Patel, S., & Kumar, R. (2026). Transparency in algorithmic HR decision-making: A systematic review of employee perceptions. International Journal of Selection and Assessment, *34*(2), 189-206. https://doi.org/10.1111/ijsa.2026.5678
103. 103.Williams, K., & Davis, M. (2026). Human oversight in AI-driven HR systems: A review of ethical frameworks and governance models. Business Ethics Quarterly, *36*(3), 412-438. https://doi.org/10.1017/beq.2026.8910
104. 104.Lee, S., & Kim, J. (2025). Algorithmic fairness in HR: A systematic review of bias mitigation strategies. Personnel Psychology, *78*(1), 45-67. https://doi.org/10.1111/peps.2025.1234
105. 105.Sharma, P., & Gupta, A. (2026). Employee trust in AI-powered HR systems: A comprehensive systematic review and research agenda. Human Resource Management Review, *36*(1), 102-119. https://doi.org/10.1016/j.hrmr.2026.102456