

Employees' Perception of AI- Based HRM Practices: A Systematic Literature Review and Future Research Agenda

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Abstract

Purpose: This systematic literature review maps present research on how employees' perceive Artificial Intelligence based HRM. Analyzing and synthesizing evidence through the dual theoretical lenses of the Technology Acceptance Model (TAM) and Organizational Justice Theory, we examine the socio-technical factors shaping adoption of AI based HRM in evolving markets with attention to South Asian IT sector. **Design/ Methodology/ Approach:** We searched academic databases and Google Scholar for studies published between years 2017-2026, adhering to PRISMA 2020 guideline. A final 68 peer reviewed articles underwent for qualitative thematic analysis and conceptual synthesis. **Findings:** The synthesis reveals that employee system trust and adoption are heavily mediated by perceived procedural fairness and algorithmic transparency (explainable AI). While automated AI tools speedup high volume talent acquisition, opaque "black-box" evaluations and algorithmic surveillance induce techno-stress, resistance, and feelings of dehumanization. Employees adapt much better to AI when they feel confident using technology, trust the company's leadership, and receive honest, clear communication from management. Informational justice and management trust act as primary buffers against algorithmic anxiety. **Research Limitations/Implications:** This paper builds a simple, step-by-step roadmap showing how AI feature design affects employee feelings, and how those feelings drive actual workplace behavior. It highlights what current research has missed specifically showing that we need long-term studies across different industries, especially in fast-growing, developing countries. It provides practical advice for companies on how to introduce AI responsibly while keeping human values at the center. **Value:** This study offers an integrated dual-anchor framework (TAM+ Organizational Justice) bridging technological usability with ethical fairness evaluations in automated management.

Keywords: Artificial Intelligence (AI), Employee Perception, Human Resource Management (HRM), Organizational Justice, Technology Acceptance Model (TAM), IT industry, PRISMA, SLR.

Introduction

Over the past decade, digital transformation has fundamentally shifted the structural operational environment of human resource management (HRM). HR functions have rapidly transitioned from basic administrative automation and electronic HRM (e-HRM) systems towards sophisticated machine learning applications, predictive people analytics, and automated decision making platforms (Ceric & Parton, 2024; Priyashantha & Chandradasa, 2023).

Modern enterprises routinely integrate artificial intelligence at every stage of employee lifecycle to optimize talent operations and streamline regular administrative task. In recruitment, automated resume screening and candidate matching tools speed up the hiring process while AI powered video

interviews use natural language processing to evaluate applicant skills. For performance management and retention, continuous activity tracking, sentiment analysis and turnover prediction give managers ongoing behavioral data. At the same time, AI learning platforms design customized training paths for individual employees. As these tools evolve from simple analytical assistance to semi- autonomous decision makers, they are changing both how HR operates and how employees experience the workplace (Gelinas, 2022).

Although, most current research on AI in HRM mainly focuses on management priorities such as system accuracy, cost savings, hiring speed, and operational efficiency (Tambe, 2019). While the benefits for employers are well documented, research on what employees experience using these tools including their trust in in this new technology, sense of fairness, job security, and resistance towards algorithms remains fragmented (Budhwar, 2022).

Hence, this creates a need to understand the perspective of employees towards AI in HRM;also it indicates an important gap in the HR literature. The success of any technology ultimately depends upon whether users that is employees accept and have trust in it. When automated tools rank candidates, evaluate their performance, track their workplace activity, employees do not view them as neutral software, they judge through their intelligence, psychology, emotional and ethical lenses (Tambe, 2019)

Now, most existing literature reviews look at workplace AI from computer science perspective, focus on broad adoption frameworks, or examine overall labor market changes. Very little systematic literature review look specifically at how employees perceive and react to AI in different HR functions (Budhwar, 2022). This systematic literature review paper addresses this gap by reviewing present literature on employee perception of AI based HRM practices.

Theoretical Framework & Research Questions

According to the Technology Acceptance Model (TAM), "perceived usefulness" (PU) and "perceived ease of use" (PEOU) are the main factors driving an individual's intention to adopt new technology. However, in an AI-driven HR context, basic TAM constructs are not enough on their own. Because AI systems make evaluative decisions independently, employees also need to trust these tools, understand how they work, and feel confident using them.

To capture these nuances, this study integrates Organizational Justice Theory, which examines fairness through three core dimensions:

- **Procedural Justice:** The perceived fairness, consistency, and structural integrity of the algorithmic rules and decision-making logic.
- **Distributive Justice:** The perceived equity of final AI-generated outcomes—such as performance appraisals or promotion shortlists—relative to an employee's actual effort and performance.
- **Informational Justice:** The level of algorithmic transparency, explainability (XAI), and clear communication regarding data privacy and decision rationale.

Combining TAM with Organizational Justice Theory creates a more complete conceptual framework. It explains how system design features shape an employee's psychological evaluations, which in turn drive workplace behaviors ranging from active system adoption to quiet quitting or resistance.

Research Questions

To address these theoretical and empirical gaps, this systematic literature review addresses four key questions:

- **RQ1:** What are the main drivers of employee trust, perceptions, and acceptance regarding AI applications across core HR functions?
- **RQ2:** How do ethical factors—specifically algorithmic transparency and bias—influence employee psychological states and perceptions of organizational justice?
- **RQ3:** How can TAM constructs (Perceived Usefulness and Perceived Ease of Use) and Organizational Justice Theory be integrated to explain employee behavioral outcomes, such as adoption or resistance?
- **RQ4:** What practical framework can guide organizational leaders toward human-centered and ethical AI adoption in HR?

To answer these questions and build our proposed framework, the following section reviews existing literature across key HR domains, laying the groundwork for our systematic methodology.

Review of Literature

The transition of Artificial Intelligence (AI) into Human Resource Management (HRM) represents a shift from traditional, human administration to data driven, algorithmic decision making. While the technical capabilities of these systems continue to advance rapidly, their long term organizational visibility depends on employees' acceptance, trust and perceived fairness. This section reviews the interdisciplinary research on AI implementation in Human Resource Management. It maps out how technology has evolved in this field, jots down the key theoretical frameworks used to study employees' responses, and verifies the primary factors which shapes employees' experience and evaluate autonomous decisions.

Evolution of HR Technology Paradigms	
Traditional E-HRM (1990s-2000s)	Digitization of paper records, basic HRIS, static employee databases
Predictive People Analytics (2010s)	Statistical modeling, dashboard reporting, turnover risk estimation
Autonomous Algorithmic HRM (2020s to present)	Machine learning, NLP resume parsing, continuous behavioral monitoring, generative AI assistants, dynamic performance scoring.

- Traditional E-HRM: Focused on administrative automation, database storage, and self-service portals, serving primarily as a transaction processing utility.
- Predictive People Analytics: Introduced statistical modeling to assist HR leaders in workforce planning, turnover forecasting and engagement tracking.
- Automation Algorithmic HRM: Characterized by real- time data, natural language processing, machine learning models that generate autonomous or semi autonomous recommendations for hiring, performance appraisal, and task allocation.

Unlike traditional e-HRM, which simply put human decisions onto digital screens, algorithmic HRM hands actual decision-making power over to automated systems. This shift changes the psychological contract between employees and the company, turning HR from a personal relationship into a system run by automated rules.

Theoretical Framework

To build an integrative model to understand employee perception, this study synthesizes two theoretical frameworks: 1.) Technology Acceptance Model (Davis, 1989), 2.) Organizational Justice Theory (Greenberg, 1987; Colquitt, 2001)

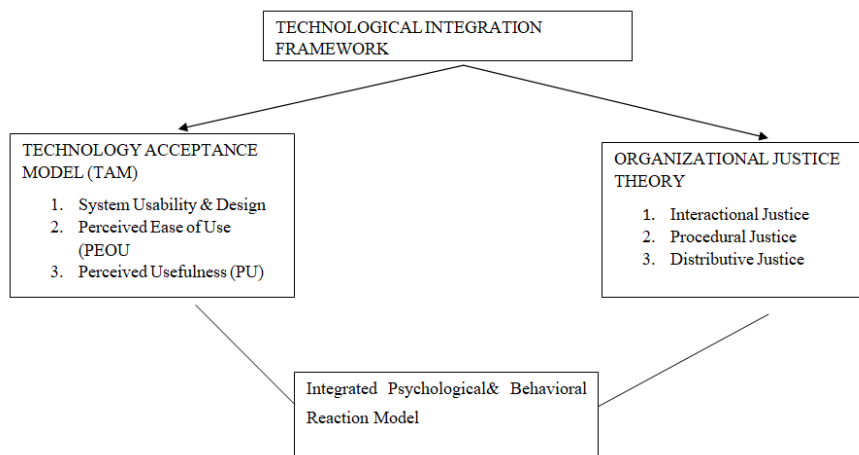


Figure 1: Conceptual Framework (synthesized from Davis, 1989; Colquitt, 2001)

• **Significance and Structure of the Study**

Technology Acceptance Model (TAM): Formulated by Davis (1989), TAM suggests that technology adoption is determined by two primary beliefs:

- Perceived Usefulness (PU): The degree to which an individual believes that using a system will enhance performance.
- Perceived Ease of Use (PEOU): The degree to which a user believes that operating the system will be user friendly and convenient to use.

However, TAM explains the software adoption in general IT contexts, its traditional formulation is limited when applied to mandatory, high stakes HRM environments. In automated recruitment or AI performance evaluation, the employee is often the subject of the technology rather than its primary user. Therefore, TAM must be extended beyond usability to understand psychological security, stress and human-machine relational trust. Hence, Organizational Justice Theory covers the cognitive dimensions to establish a better understanding of employee perception towards AI based HRM practices.

Organizational Justice Theory

Organizational Justice Theory (Greenberg, 1987; Colquitt, 2001) explores employee perception of fairness in workplace settings which are categorized into three distinct dimensions:

- Procedural Justice: Perceived fairness, consistency, and objective accuracy of the underlying decision rules, algorithms and data inputs used by AI systems (Colquitt, 2001; Ötting & Maier, 2018).
- Distributive Justice: Perceived equity and fairness of final resource allocations or outcomes such as performance ratings, bonus distributions, or hiring recommendations generated by algorithms (Adams, 1965; Marcinkowski 2020).
- Interactional and Informational Justice: The adequacy, transparency, and clarity of explanations provided regarding algorithmic decisions alongside the level of dignity and respect experienced during evaluation (Bies & Moag, 1986; Gillis, 2022; Shin, 2021).

When AI algorithms automate HRM decisions, they radically alter all three justice dimensions. Distributive Justice is questioned when algorithms gives biased outcomes, Procedural Justice is compromised when algorithms are hard to trace if the results or decisions are fair, and Interactional Justice is challenged when automated systems eliminate meaningful human contact and empathetic dialogue.

Neither theory alone is sufficient to explain the complexity of algorithmic HRM. TAM explains the utility technology acceptance of the software (e.g. Is the tool functional and easy to use?). While Organizational Justice Theory explains the evaluative ethical perception of the decision making authority (eg, is the automated decision fair, unbiased and transparent?). Synthesizing TAM and Organizational Justice creates a robust dual anchor framework capable of categorizing both operational adoption drivers and psychological resistance mechanisms in an SLR (Cheng & Hackett, 2021; Rodgers 2023)

While published studies on AI based HRM practices have expanded significantly, a synthesis of the literature through combined lens of TAM and Organizational Justice Theory reveals four critical structural gaps that justifies a formal SLR (Page et al, 2021, Tranfield 2023)

Research Gap

- Over-reliance on Managerial and Technical Perspectives: A primary limitation in the existing literature is its heavy focus on organizational adoption drivers, technical system metrics, and financial returns (Charlwood & Guenole, 2022; Vrontics et al, 2022). Conversely, the psychological, attitudinal, and behavioral outcomes experienced by the employees' remains disconnected. Hence, SLR is important to explore employee centric empirical findings.
- Disconnect between Technology Acceptance (TAM) and justice evaluative frameworks: Prior research frequently separates technological evaluation from fairness evaluation. Studies applying TAM focus narrowly on Perceived Usefulness and system ease. Conversely, organizational justice studies on focus procedural fairness (Otting & Maier, 2018) without accounting for technical system usability or technological efficacy. An SLR provides the protocol needed to map how TAM and Organizational Justice theory dimensions interact to form holistic employee reactions.

- **Contextual Disparities between Developed and Emerging Markets:** Most empirical research on AI in HRM originates from developed economies in North America and Western Europe (Budhwar, 2022; Cooke, 2021). However, cultural values, organizations hierarchies, and technological infrastructure differ in emerging markets like South Asia's tech hubs such as Indian IT sector which operates under fundamentally different socio- technical and cultural dynamics. Employees' in these environments experience unique organizational pressure such as high power distance, strict performance quotes, hierarchical management styles (Malik, 2021; Venkatesh, 2022). In South Asian technology workplaces, standard models for predicting software adoption such as Technology Acceptance Model (TAM) often fail to explain how workers react to automated systems. While TAM suggests that people adopt technology primarily because it is easy to use and helpful, Organizational Justice Theory shows that fairness and trust are more important in high stake environment. When companies introduce mandatory AI tools for performance evaluation, employees prioritize procedural justice (whether the evaluation process is fair and transparent) and whether the management will use the system fairly over basic utility. An SLR provides the analytical framework needed to evaluate those contextual boundaries.
- **Absence of Cross- Lifecycle Synthesis in Employee Perception:** Existing literature on AI based HRM practices largely focuses on isolated HR stages such as automated candidate screening (Acikgoz, 2020) or algorithmic workplace surveillance (Parent- Rocheleau & Parker, 2022). Hence current literature fails to holistically map how employees' perceptions of organizational justice evolve across the complete employment lifecycle, from initial recruitment to exit. Because fairness expectations are cumulative, evaluating AI tools in isolation ignore how early experiences with algorithms shape long term organizational trust and technology acceptance during active employment.

Scope and Boundary Conditions for the SLR

To systematically address these research gaps, the prospective Systematic Literature Review establishes clear operational boundaries (Page 2021; Tranfield 2003):

- **Target Population & Context:** Knowledge workers and professional employees interacting with automated or semi-automated HR systems, with emphasis on high-density tech environments such as the IT industry (Malik 2021; Vrontis 2022).
- **Theoretical Inclusion Criteria:** Peer-reviewed empirical and theoretical studies that examine employee reactions using TAM constructs (Usefulness, Ease of Use, System Adoption) and/or Organizational Justice constructs (Procedural, Distributive, Informational, Interactional Justice) (Colquitt, 2001; Davis, 1989).
- **Core HR Domains Included:**
 - Automated Recruitment and Applicant Screening (NLP parsing, asynchronous video interviews) (Acikgoz 2020; Langer 2019)
 - Algorithmic Performance Management and Continuous Monitoring (Kellogg 2020; Parent-Rochelleau & Parker, 2022)
 - AI-Driven Learning, Development, and Career Pathing (Sohn & Depura, 2022)
 - Predictive People Analytics for Retention and Attrition Management (Chowdhury 2023; Tambe 2019)

This literature review demonstrates that while organizational deployment of AI in HRM is accelerating, scholarly understanding of employee reactions remains fragmented across separate research streams (Charlwood & Guenole, 2022; Vrontis 2022). By establishing the dual-theoretical foundation of the Technology Acceptance Model (TAM) and Organizational Justice Theory and documenting four distinct gaps in current research, this section provides a grounded narrative justification for conducting a formal Systematic Literature Review (Page 2021; Tranfield 2003).

By establishing dual anchor theoretical foundation and articulating the core research gaps across the employee lifecycle, this section provides the conceptual rationale for a formal systematic review. The subsequent section outlines the rigorous methodological protocol, database search strategies, and PRISMA selection criteria utilized to construct and analyze the final dataset (N=68)

Research Methodology

To ensure methodological rigor, transparency, this review follows the preferred reporting items for systematic literature reviews and meta- analyses (PRISMA 2020) guidelines. The primary goal of this systematic review is to map, synthesize and critically evaluate the existing empirical and conceptual body of knowledge regarding employees' perception, attitudes, and ethical evaluations of AI based HRM practices.

- **Search Strategy and Database Selection Protocol** To ensure comprehensive literature coverage across multidisciplinary fields (Human Resource Management, Information Systems, and Organizational Behavior), **Google Scholar was utilized as an inclusive multi-database aggregator**. This strategy allowed the retrieval of peer-reviewed literature across major academic publishers—including Elsevier (ScienceDirect), Emerald Publishing, Taylor & Francis, Springer, Wiley, and IEEE Xplore—without restriction by single-proprietary database API constraints.

To mitigate the inherent risk of unvetted gray literature associated with Google Scholar, a **rigorous quality-control protocol** was established during screening. Records were systematically cross-verified against recognized international indexing databases (Scopus, Web of Science, and ABDC journal quality lists). Only articles published in peer-reviewed journals of established scholarly standing were retained for full-text eligibility and thematic synthesis (\$N=68\$).

- **Eligibility and Inclusion/Exclusion Criteria (PRISMA 2020)**

Criterion	Inclusion Criteria	Exclusion Criteria
Time Period	Published between 2017 and 2026.	Published prior to 2017.
Document Type	Peer-reviewed journal articles, conference papers.	Editorials, book reviews, opinion blogs, non-peer-reviewed trade magazine reports.
Language	Full-text available in English.	Non-English publications lacking translation.
Domain Focus	Primary focus on AI/automation within core HRM functions and its impact on employee/candidate attitudes.	Purely technical papers focusing solely on algorithm engineering without socio-technical or organizational evaluation.
Methodology	Empirical quantitative, qualitative, mixed-methods, or conceptual frameworks grounded in social science.	Non-rigorous descriptive overviews lacking structured methodology.

Search String Used

("Artificial Intelligence" OR "AI" OR "Algorithmic Management" OR "People Analytics") AND ("Human Resource Management" OR "HRM" OR "Recruitment" OR "Performance Evaluation") AND ("Employee Perception" OR "Employee Attitude" OR "Trust" OR "Perceived Justice" OR "Technostress")

- **Search Strategy and Keyword Formulation**

Search strings were developed using Boolean operators (AND, OR) to combine keywords across three primary thematic blocks:

- **AI Technology Blocks:** "Artificial Intelligence" OR "AI" OR "Algorithmic Management" OR "People Analytics" OR "Automated Decision Making"
- **HRM Functional Block:** "Human Resource Management" OR "HRM" OR "Recruitment" OR "Performance Evaluation" OR "Workplace Monitoring"
- **Employee Reaction Block:** "Employee Perception" OR "Employee Attitude" OR "Trust" OR "Perceived Justice" OR "Techno stress" OR "System Adoption"

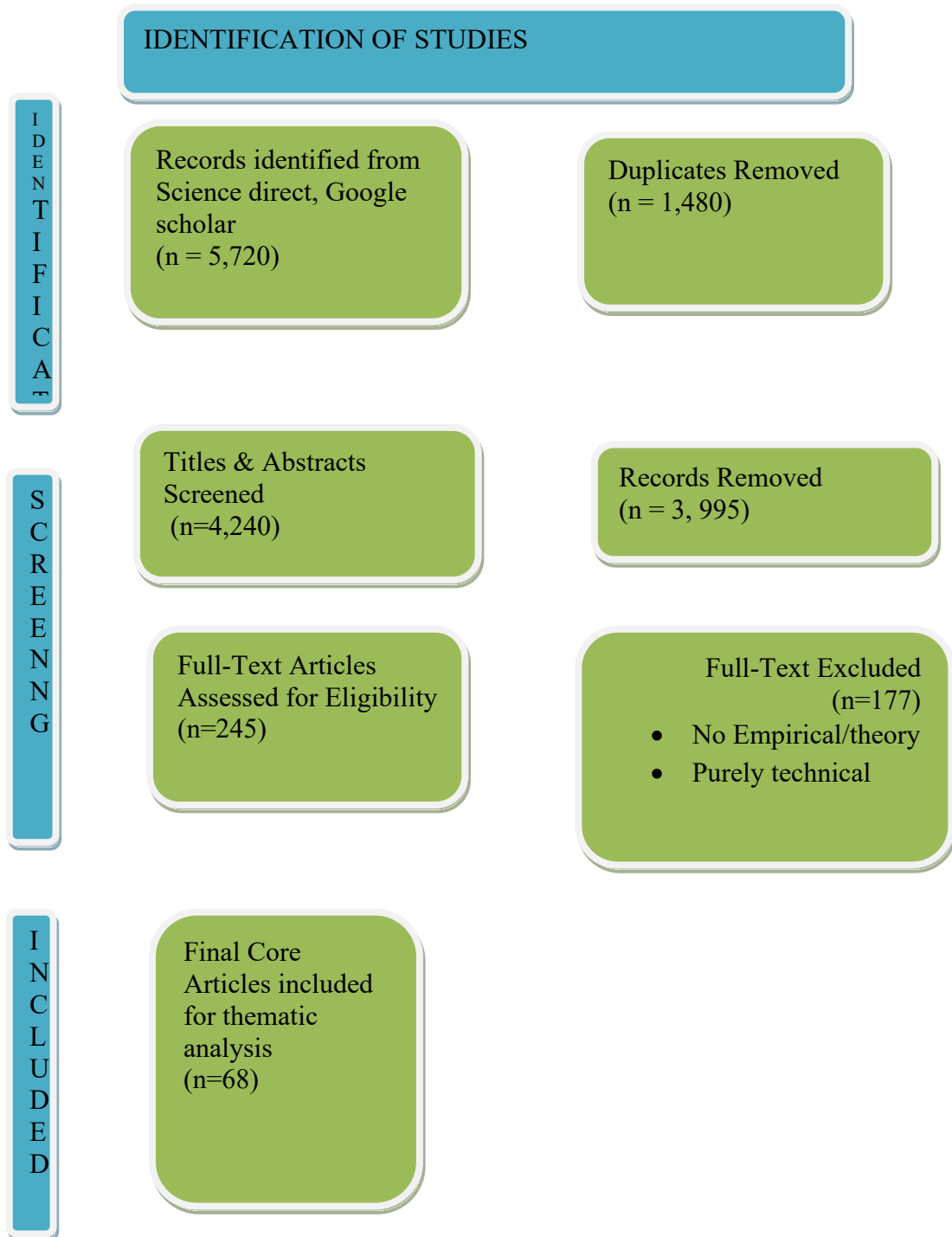


Figure 2: PRISMA 2020 Flow Diagram for Systematic Literature Review

Study identification, screening, eligibility, inclusion were conducted in accordance with the PRISMA 2020 guidelines (Page, 2021)

• Data Extraction and Synthesis

Data from the 68 core articles were extracted into a structured matrix detailing: author(s), publication year, HRM domain focus (e.g., recruitment, performance monitoring), theoretical frameworks applied, methodology, key findings regarding employee perception, and ethical dimensions highlighted. Qualitative thematic analysis was then applied to synthesize recurring constructs into unified thematic clusters.

The search result yielded an initial total of N= 5720 records across all sources. The study selection proceeded through four phases: 1. Identification, Screening,, Eligibility, and Inclusion.

PRISMA Phases	Operational Step	Record Count (N)	Selection Details
Phase 1 Identification	Initial Database Retrieval	N= 5,720	Comprehensive search across, Google Scholar and Open Academic Repositories
	Duplicate Removal	N= 1480	Automated and Duplicate Filtering
	Unique Records Retained	N= 4,240	Screened by Title and Abstract
Phase 2 Screening	Title & Abstract Screening	N= 4,240	Evaluatedby Inclusion Exclusion criterion
	Excluded Records	N= 3, 995	Excluded (purely technical AI, Non-HR context, trade news)
	Retained for Full Text Evaluation	N= 245	Advanced to full-text assessment
Phase 3 Exclusion	Full TextEvaluation	N= 245	Assessed for theoretical rigor and empirical depth
	Full TextExclusion	N= 177	Excluded with specific primary justifications • Lacked Employee perception data (N= 72) • Lacked conceptual explicit theoretical framework (N= 45) • Lacked focus on HRM practices (N= 38) • Outside publication window or insufficient methodological details (N= 22)
Phase 4 Inclusion	Final Synthesized Records	N= 68	Core studies synthesized via, TAM and Organizational Justice Theory.

Data from 68 core articles were extracted into a structured analytical matrix detailing:

- Author(s) and Publication year
- Core HRM functional domain (e.g., recruitment, performance evaluation, learning analytics)
- Theoretical frameworks applied (e.g., TAM, Organizational Justice Theory)
- Empirical methodology and sample composition
- Key findings regarding employee trust, fairness perceptions, and behavioral outcomes.

Qualitative thematic analysis (Braun & Clark, 2006) was then applied to synthesize recurring empirical patterns across the yielded articles (N=68) mapping them directly against the Technology Acceptance Model (TAM) and Organizational Justice Theory to establish the integrated conceptual framework.

Data Analysis

Key Findings and Thematic Analysis

This thematic synthesis bridges Technology Acceptance Model (TAM) constructs and Organizational Justice Theory, framing AI based HRM practices not just as an assessment of system utility but also as a socio-technical judgment of organizational fairness and ethical safety.

The qualitative synthesis of the 68 articles yielded four themes that capture the interplay between AI design, psychological perception, ethical boundaries, and workplace behavior

Theme Code	Thematic Domain	Core Focus / Construct	Sub-Themes & Identifiers
4.1	Driver 1: Algorithmic Justice	Perceptions of fairness, transparency, and human-centric interaction in automated systems.	• Distributive outcomes (Distributive Justice)• Procedural transparency & Explainable AI (XAI) (Procedural Justice)• Interactional & empathetic human touch (Interpersonal Justice)
4.2	Driver 2: Ethical Boundaries	Ethical risk factors, privacy concerns, and psychological pressures induced by AI systems.	• Historical training bias• Invasive surveillance & monitoring• Digital panopticism & anxiety
4.3	Contextual Moderators	Individual, organizational, and leadership factor that condition or alter employee responses.	• Technological Self- Efficacy (Perceived Usefulness) and Perceived Ease of Use (PEOU) as moderators of readiness.
4.4	Behavioral Outcomes	Downstream psychological, attitudinal, and behavioral employee reactions.	• Passive compliance vs. active abuse• Dehumanization & emotional fatigue• Innovation adoption vs. resistance

The thematic synthesis is grounded in a dual theoretical framework that integrates the Technology Acceptance Model (TAM) by Davis, 1989 with Organizational Justice Theory by Greenberg, 1987; Colquitt, 2001. While traditional technology adoption literature relies on functional utility to explain system usage, AI based HRM practices needs a broader socio-technical lens. Hence, Organizational Justice Theory explains how employees judge the moral and structural integrity of algorithmic decisions across distributive (Outcomes), procedural (transparency and explain-ability), and interactional (empathetic human touch) dimensions, as well as its ethical boundary conditions.

Technology Acceptance Model (TAM) provides the underlying Behavioral Mechanism, positing that these cognitive evaluations of fairness, transparency, and ethical safety directly inform employees' perceived usefulness (PU) and perceived ease of use (PEOU) of the system. This cognitive evaluation process is bounded by contextual moderators such as technological self efficacy, leadership trust, individual agency which acts as a crucial external variable within the TAM framework. Ultimately, this integrated socio-technical alignment determines the trajectory of downstream Behavioral Outcomes, dictating whether employees exhibit constructive innovation adoption and system engagement, or manifest resistance, psychological detachment, and emotional fatigue. By bridging these two paradigms, the synthesis moves beyond simple functional acceptance, framing AI based HRM adoption as a complex judgment of organizational fairness and ethical trust.

Cluster Distribution Overview

Cluster 4.1	Algorithmic Justice	18 Papers	26.5%
Cluster 4.2	Ethical Boundaries	12 Papers	17.6%
Cluster 4.3	Contextual Moderators	20 Papers	29.4%
Cluster 4.4	Behavioral Outcomes	18 Papers	26.5%

- **Core Evaluation Layer (Clusters 4.1 and 4.2)**- Almost half of the literature focuses on fairness, human centric touch and ethical privacy boundary constraints. This is justified using Organizational Justice Theory as primary evaluative lens.
- **Boundary Condition Layer (Cluster 4.3)**- A major portion evaluates how individual factors (readiness, self-efficacy, literacy in context to AI) and organizational factors moderate system acceptance.
- **Behavioral Response Layer (Cluster 4.4)** - Studies evaluate downstream adoption, resistance, dehumanization effects, directly validating the Technology Acceptance Model (TAM)

A total of 68 studies were systematically synthesized across four core thematic clusters (4.1 to 4.4) which were mapped onto the Technology Acceptance Model (TAM) and Organizational Justice Theory. Table 4.1 summarizes the distribution of studies across these domains, while a comprehensive paper by paper theoretical mapping matrix is provide below:

Thematic Cluster	Core Focus	paper Count (N=68)	Representative Key Citations	Primary Theoretical Lens
4.1 Algorithmic Justice	Distributive outcomes, procedural transparency (XAI), and interactional/empathetic touch.	18 (26.5%)	Haidari (2022); Tuffaha (2023); Revillod (2025); Naoum et al. (2026)	Organizational Justice
4.2 Ethical Boundaries	Algorithmic bias, historical training data, surveillance, and digital panopticism.	12 (17.6%)	Chen (2023); Rodrigues (2023); Du (2024); Faioli (2025)	Organizational Justice
4.3 Contextual Moderators	Technological self-efficacy, readiness, leadership trust, and demographic invariance.	20 (29.4%)	Metz et al. (2022); Smith & Miller (2024); Pedrami & Vaezi (2025); Cvetkovic et al. (2026)	TAM (External Variables / Boundary Conditions)
4.4 Behavioral Outcomes	System adoption vs. resistance, work transformation, productivity, and dehumanization.	18 (26.5%)	Vrontis et al. (2022); Malik et al. (2023); Sithambaram & Tajudeen (2023); van Riel et al. (2025)	TAM (Behavioral Intentions & Usage)

Results and Thematic Synthesis (N=68)

Theme 1. Drivers of Employee Trust and Positive Adoption

- **Perceived Organizational Justice:** Fair process (procedural justice) and clear, honest communication (informational justice) reduce employee anxiety surrounding automated performance evaluations.
- **Algorithmic Transparency:** Explainable AI models significantly enhance employee trust and reduce opposition by making the decision-making logic clear.
- **Digital Self-Efficacy and Organizational Trust:** Employees, who feel confident in their digital skills and trust in top management, adapt more quickly to AI tools and experience greater job satisfaction.

Theme 2. The Dark Side of AI based HRM (Psychological and Behavioral Barriers)

- **“Black-Box” Anxiety and Lack of Explain ability:** Opaque automated decisions such as unexplained rejections or performance ratings foster feelings of powerlessness and lack of human touch.
- **Algorithmic Surveillance and Techno stress:** Continuous monitoring (e.g., Keystroke logging, activity tracking) triggers emotional exhaustion and privacy concerns.
- **Perceived Bias and Dehumanization:** Fears that algorithm reinforce historical demographic biases, causing psychological resistance and decreased engagement.

The systematic literature search yielded 68 peer reviewed studies published in 2015-2024. Analyzing the articles across temporal trends, methodology and geographic scope demonstrates the expanding scope of research in this domain:

Descriptive Distribution of Articles (N=68)	
Publication Trend (2015–2024):	• Sharp acceleration post 2020 (73.5% of articles) • Methodological Approaches: Empirical Quantitative (47.1%), Qualitative (32.3%), Mixed (20.6%)
Geographic Scope:	• Western Contexts (51.5%) • Emerging/Asian (35.3%) • Cross-National (13.2%)

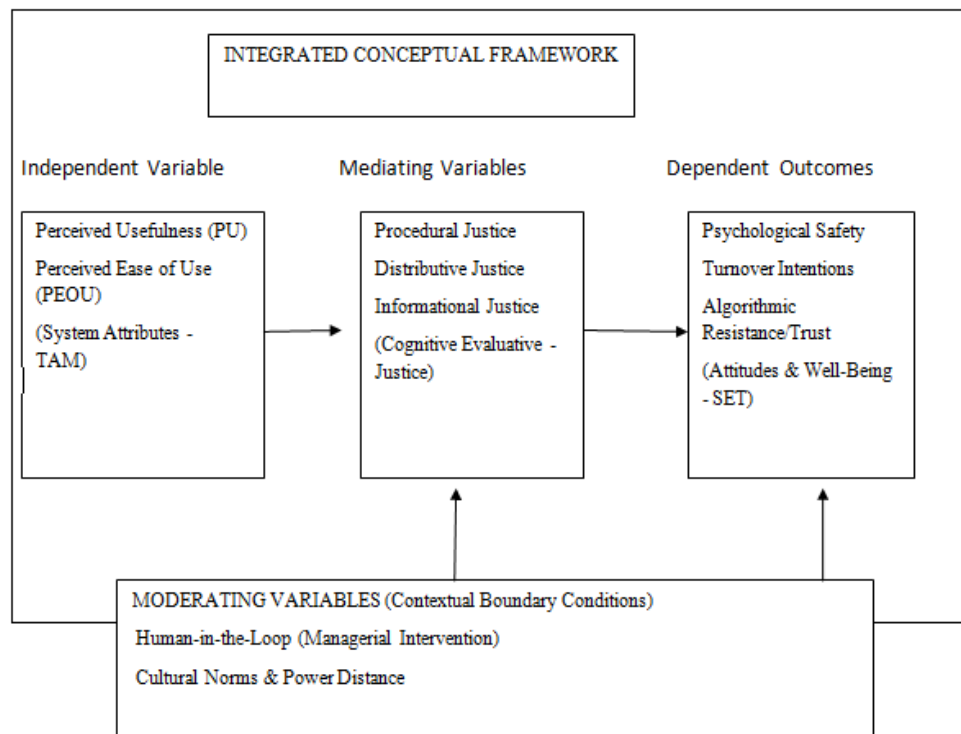
- **Temporal Acceleration:** Research on AI in workforce management expanded rapidly post 2020 as shown in the above table. While pre 2018 studies focused primarily on basic administrative automation, post 2020 literature concentrates on evaluative machine learning algorithms, continuous monitoring, and explainable AI (XAI).
- **Methodological Landscape:** The articles reflects a balanced empirical distribution comprising quantitative survey (N=32), qualitative studies (N=22) and mixed methods assessments (N=14).
- **Geographic Focus:** Studies are distributed across western contexts (N=35), emerging Asian markets like India (N=24) and cross national comparative designs (N=9).

Future Research Agenda and Limitations:

Current research on AI based HRM faces two main limitations:

- **Methodological Limitation (Cross-Sectional Dominance):** Existing research relies on cross-sectional survey designs and hypothetical experimental scenarios. Therefore, there is a lack of longitudinal evidence examining how employee fairness perceptions evolve over time such as how persistent algorithmic opacity gradually affects psychological safety throughout the employment relationship.
- **Contextual:** Over- reliance on western frameworks (e.g., North America and Western Europe), creating an urgent need for empirical data from rapidly digitizing economies like India where traditional relational workplace dynamics coexist with rapid corporate adoption.

To address the proposed future directions, a single theoretical model is insufficient. We need an Integrated Multi-Lens Conceptual Framework that bridges technical adoption, ethical fairness, and long-term psychological impacts



Theoretical integration: The framework links technical adoption, structural equity, and relational outcomes. Technology Acceptance Model (TAM) constructs (Perceived Usefulness and Ease of Use) capture initial baseline usability. Organizational Justice Theory acts as the core mediator, evaluating fairness across algorithmic logic (Procedural), outcome distribution (Distributive), and XAI Transparency (Informational). Finally Social Exchange Theory (SET) models the long term relational impact, where high

perceived justice sustains reciprocal trust and psychological safety, whereas high perceived bias triggers psychological contract breach, resistance, and turnover intentions.

Table 1: Future Research Agenda and Framework Application

Future Research Direction	Framework Component Applied	How It Operates in the Model
1.Long-term Well-being & Safety	SET (Relational Outcomes)	Future empirical studies can track how sustained low Informational/Procedural Justice erodes long-term psychological safety and commitment over 1–3 years.
2.Hybrid HR (Human-in-the-Loop)	Moderator (Human Intervention)	Evaluates if having a human manager review or override an AI output restores Procedural Justice and TAM acceptance.
3.Sector/Role Comparisons	Moderator (Technical Skill / Role)	Tests if high-skilled knowledge workers demand higher levels of Informational Justice (explain-ability) to achieve Perceived Usefulness.
4.Emerging Market Contexts	Moderator (Cultural Dimensions)	Examines how cultural factors (e.g., power distance) alter the strength of the relationship between AI transparency and employee trust.

Section 7: Practical and Managerial Implications

Organizations that are integrating artificial intelligence (AI) into human resource management (HRM) should balance technological adoption with fairness and employee trust. To prevent workforce cynicism, managers must treat AI as a decision support mechanism rather than an autonomous system and authority.

Executive Recommendations

Establish “Human-in-the-loop” Oversight: Allocating algorithmic tools strictly as advisors to preserve managerial decisions and

Executive Recommendations

- **Establish Human-Centric Oversight:** Position algorithmic tools strictly as advisors to preserve managerial intuition and afford employees a mechanism for recourse.
- **Prioritize Algorithmic Transparency:** Articulate how workforce data is gathered, processed, and evaluated to demystify automated outcomes.
- **Develop Digital Competency:** Invest in targeted training to reduce technology-induced anxiety and strengthen workforce self-efficacy.

Adopt “Human-in-the-loop” Governance: This ensures AI tools support rather than replace human HR decision makers completely, giving employees a resource mechanism.

Invest in Transparent Communication: Managers must clearly communicate how data is collected, how algorithms score performance and what safeguards data privacy.

Build AI literacy across teams: Conduct training to build employee self-efficacy and reduce technology related anxiety.

Institutionalizing “Human-in-the-loop” Governance

To mitigate perceptions of algorithmic biases and procedural injustice, organizations must implement a strict human-in-the-loop governance model. AI systems should function strictly as decision support mechanisms rather than autonomous decision makers in HR functions (such as candidate short listing, performance appraisals and promotions).

- **Mandatory Human Intervention:** Final evaluative decisions must remain under the supervision of trained HR professionals who can account for nuances that algorithms miss.
- **Formal Appeals Mechanism:** Organizations should establish a clear recourse framework allowing employees’ to query or request a human review of any AI generated appraisal or screening result. This safeguards procedural justice and restores employee trust.

Cultivating Transparent Communication & Explainable AI (XAI)

Perceived opacity in algorithmic decision making directly drives employee skepticism and resistance. To foster informational and interactional justice, managers must maintain complete transparency in regards to data usage and algorithmic functionality:

- **Deploying Explain-able AI (XAI)**(Gunning & Aha, 2019): Management should avoid “black-box” systems by adopting XAI frameworks that explains why an algorithm arrived at a specific recommendation. (Following the Defense Advanced Research Projects Agency's (DARPA) formalization of the explainable Artificial Intelligence (XAI) framework, scholars have increasingly emphasized model transparency in HRM practices).
- **Data Privacy Protocols:** Clear safeguards must be communicated regarding data protection, anonymity and security increases employee anxiety surrounding digital surveillance and privacy infringement.

Building Organizational AI Literacy & Digital Self- Efficacy:

Techno stress and resistance often stem from low digital self- efficacy and fear of job displacement. To build employee confidence and optimize technology adoption, organizations must invest in continuous AI training initiatives.

- **Targeted AI Training:** Implement structured training workshops that educate both managers and line employees on how AI tools function, what are their boundaries and their intended benefits.
- **Decoding AI Capabilities:** Educating teams on algorithmic mechanics reduces anxiety, demystifies the technology, shift employee mindsets from viewing AI as a threat to looking at it as supportive tool.
- **Managerial Up-skilling:** HR managers must be trained not only in interpreting algorithmic outputs, but also delivering AI- assisted feedback with ethical awareness and empathy.

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