

Systematic Literature Review on the Relationship between Employee Engagement and Artificial Intelligence



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1. ABSTRACT

This paper is a Systematic Literature Review (SLR) where we look at the complex relationship between Employee Engagement (EE) and Artificial Intelligence (AI), specifically Generative AI (GenAI) and the objectives. In this review, the study has examined 133 scholarly works, including studies based on experiments and concepts, to come up with the dynamic research landscape in this field. Outcomes indicate a steep increase in the field of research on relationship between Artificial Intelligence and Human Resource from 2016, with a significant increase on research in this area after the COVID-19 pandemic. This literature review is based on the Job Demands–Resources (JD-R) framework, analysing the increase in engagement, productivity, and satisfaction, by increasing efficiency and GenAI adoption as job resources. In parallel we also look at AI-induced technostress as a job demand that contributes to exhaustion and work–life imbalance. This study looks at how the evolution of Generative AI has helped in transforming the impression of HR from being administrative to more strategic by automating repetitive tasks, facilitating HR professionals focus on engagement of employees and building organizational culture. Employee Experience has increased over time and sustained engagement have been reinforced by useful applications of AI in areas like predictive analytics for attrition forecasting, structured learning programs and instantaneous feedback mechanisms. This review also emphasises current ethical challenges like reduction in algorithmic bias, maintenance of data transparency and privacy, and addressing employee anxieties regarding job security and trust thereby ensuring a human touch in deployment.

Key Words Artificial Intelligence, Employee Engagement, Human Resources

2. INTRODUCTION

The Digital Redefinition of Employee Engagement

Today's workforce is experiencing the main transition because of the fast convergence between Artificial Intelligence (AI) and intelligent automation (Bastida et al., 2025; Dinesh Kannaa and Karthika, 2024; Vrontis et al., 2022). This evolution is incredibly based on Human Resource Management (HRM), because technologies of AI move from the administrative automation level to affect the strategic functionality directly, mainly employee engagement (EE) (Arora and Damarla, 2025; Malik et al., 2023; Úbeda-García et al., 2025). Employee engagement has broadly been discovered to be the major psychological condition consisted of vigor, dedication, and immersion in work with an obvious relation to better organizational performance, productivity, and turnover decrease (Kahn, 1990; Macey and Schneider, 2008; Schaufeli et al., 2002; Sundari et al., 2024; Úbeda-García et al., 2025).

The papers mention the potential of AI in bringing about the revolution of EE through personalized communication, active screening for risk factors, and real-time counseling (Arora and Damarla, 2025; Dinesh Kannaa and Karthika, 2024; Mer and

Srivastava, 2023). Generative AI (GenAI)—those who can generate human-like output (Hariri, 2023; Vaswani et al., 2017; Weng and Aguinis, 2024)—has also hastened this disruption, and it has also provided us with tools in the form of smart HRM assistants and creative coworkers (Aramali et al., 2025; Krakowski, 2025).

2.1 Research Context and Motivation

Although awareness of the strategic value of AI to HRM (Tambe et al., 2019; Úbeda-García et al., 2025) grows, the research literature contains inconsistent findings regarding employee well-being and long-term commitment (Chuang et al., 2025). Even though some unambiguous strengths in the form of stepped-up efficiency and customized developmental experiences (Sundari et al., 2024) exist, new psychological stresses, moral dilemmas, and socio-technical mismatches (Arora and Damarla, 2025; Úbeda-García et al., 2025; Yanamala, 2023) develop. To bridge theoretical potential and empirically substantiated results a synthesized integration is needed due to the fast pace of technological diffusion (Bastida et al., 2025; Chuang et al., 2025). Scholars have suggested that, as AI incorporation accelerates, academic understanding of the

multidimensional effects upon the workplace "social and emotional architecture" remains fragmented (Gómez Gandía et al., 2025; Úbeda-García et al., 2025).

2.2 Research Objectives

The Systematic Literature Review in this paper looks to address the issue highlighted above by conducting a structured, evidence-led analysis of employee engagement and AI. Based on the articles reviewed, the aims are:

- To map the methodological and intellectual structure of AI/HRM research, specifically identifying the maturity and evolution of engagement-related themes (Úbeda-García et al., 2025; Ossiannilsson et al., 2024).
- In an attempt to provide the theoretical grounds to investigate AI impacts on EE, based purely upon the dual function challenged by the Job Demands-Resources (JD-R) model (Chuang et al., 2025; Bakker and Demerouti, 2007).
- In order to conceptualize and explore how AI and GenAI job resources work to actively boost engagement through individualization, work function optimization, and LandD (Arora and Damarla, 2025; Malik et al., 2023; Noerman et al., 2025).
- In a systematic approach to investigate and explore AI as a work prerequisite, analyzing technostress, job insecurity, and resistance impacts towards engagement and work-life outcomes (Chuang et al., 2025; Aramali et al., 2025; Pan and Froese, 2023).
- In order to amalgamate the key ethical and governance issues (bias, privacy, transparency) that imperil employee trust and resultant engagement in AI-medium workplace (Arora and Damarla, 2025; Gómez Gandía et al., 2025; Yanamala, 2023).
- Specify directions for potential empirical studies and real-world methods of designing human-centric AI regulation (Bastida et al., 2025; Weng and Aguinis, 2024; Xiao and Yanghong, 2024).

3. METHODOLOGY

Mapping the Intellectual Landscape of AI and Employee Engagement

The SLR looks at adopting a rigorous, multi-stage methodology derived from the synthesis of methodological frameworks available within the literature reviewed. The approach follows proven protocols for systematic reviews (Tranfield et al., 2003) and bibliometric analysis (Donthu et al., 2021; Úbeda-García et al., 2025).

3.1 SLR Protocol and Data Sources

The earlier academic appraisals in this convention are emphatic about appropriate procedures, with

several of them following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses protocol in order to facilitate clarity and reproducibility (Bositkhanova and Dadaboyev, 2025; Obi et al., 2025; Rahim et al., 2025).

- Database Selection:** Most common databases adopted are Scopus and Web of Science (WoS) (Obi et al., 2025; Úbeda-García et al., 2025; Ammirato et al., 2024). WoS is commonly opted for due to the standardized bibliographic records (Úbeda-García et al., 2025). A broader list of reviews also encompasses Google Scholar and ScienceDirect to have full coverage (Bositkhanova and Dadaboyev, 2025; Mirtaheri et al., 2026; Obi et al., 2025).
- Search Strategy and Scope:** Typical searches entail a combination of "Artificial Intelligence" or equivalent words (e.g., "machine learning," "deep learning," "Generative AI," "Neural network*") with "Human Resource Management" ("HRM") (Ossiannilsson et al., 2024; Úbeda-García et al., 2025). Attempting to specifically focus on engagement, this review compiles literature with terms such as "Employee Engagement," "Employee Experience," "Job Satisfaction," and "Work-Life Balance" (Arora and Damarla, 2025; Chuang et al., 2025; Gómez Gandía et al., 2025; Sundari et al., 2024). The crucial time period under focus spans the first paper documented in 2002 up to 2024/2025, thus achieving a record reflecting the exponential growth in the area (Úbeda-García et al., 2025).

3.2 Analytical Techniques and Thematic Mapping

The final result relies on both macro-level bibliometric trends and micro-level qualitative analysis, capturing the methods used in the source studies (Gómez Gandía et al., 2025; Úbeda-García et al., 2025).

3.2.1 Bibliometric Analysis

By applying bibliometric techniques, the underlying academic structure and theoretical framework of the area of study can be identified (Ossiannilsson et al., 2024).

- Growth Pattern:** The relationship between Artificial Intelligence and HRM has seen a steep increase from 2016 onwards especially post COVID – 19 pandemic (Úbeda-García et al., 2025). A study following 491 pieces in 2014-2023 documented an average contribution growth rate per year as 24.57% (Ossiannilsson et al., 2024).
- Thematic Convergence:** Through VOS viewer and co-word analysis, research confirms a high degree of convergence around the following themes linking AI with employee behaviour, trust, digital leadership, and organizational culture (Gómez Gandía et al., 2025). More specifically, the key themes identified in the

broader AI/HRM area are the working experience personalization and predictive analysis (Úbeda-García et al., 2025).

3.2.2 Qualitative and Empirical Analysis

Qualitative descriptive methods, based on in-depth textual analysis, are typical for maintaining conceptual dynamics (Compagnucci et al., 2025; Sundari et al., 2024).

- a. **Use of JD-R Model:** The JD-R model (Bakker and Demerouti, 2007) is adopted as a conceptual lens for empirically testing mediating activities of engagement and exhaustion between productivity outcomes and AI-employee interaction (Chuang et al., 2025). The framework helps to justify previous productivity and job satisfaction paradoxes found in the literature (Chuang et al., 2025; Charlwood and Guenole, 2022).
- b. **Sentiment Analysis:** In methodologies for research, engagement is even measured with the help of AI itself. Sentiment analysis (SA) natural language processing-based frameworks are suggested to process the feedback received from employees via channels such as performance appraisals and mails, converting passive feedback into actionable statistics (Ali and Somu, 2023; Garg et al., 2021; Nayak, 2024). SA facilitates the detection of minute indications of disengagement or dissatisfaction and proactive targeted interventions can be designed against them (Arora and Damarla, 2025; Hinge et al., 2023b; Lee and Song, 2024).

3.3 Methodological Gaps and Limitations of Existing Research

Although analytical rigor is excellent for most studies, a significant maturity gap is faced (Úbeda-García et al., 2025; Bositkhanova and Dadaboyev.

- **Lack of Empirical Evidence:** The majority of work on AI applications in workforce planning is conceptual (7 out of 13 studies that were under review) and, therefore, the typically discussed benefits, like increased involvement and turnover reduction, are usually presumptive rather than conclusive (Bositkhanova and Dadaboyev, 2025; Úbeda-García et al., 2025).
- **Cross-Sectional Bias:** A majority of empirical work is based on cross-sectional data, which restricts deriving robust causal inference about enduring changes in engagement across time (Noerman et al., 2025; Chuang et al., 2025). The particular studies are requested specifically to capture engagement metrics prior to and following implementation of AI (Chuang et al., 2025; Úbeda-García et al., 2025).
- **Geographical and Cultural Constraints:** Also geographically constrained is a level of high-impact empirical work (e.g., with Taiwan, Chinese SMEs, or in the Indian example) (Chuang

et al., 2025; Noerman et al., 2025; Shinde, 2025a), which can have an effect on the ability to generalize findings across various organizational and cultural settings (Chuang et al., 2025; Úbeda-García et al., 2025).

4. CONCEPTUALIZING EMPLOYEE ENGAGEMENT AND THE JD-R FRAMEWORK

Employee engagement is a favourable, fulfilling, work-directed psychological state characterized by vigour, involvement, and commitment (Schaufeli et al., 2006; Schaufeli et al., 2002). A key motivator behind organizational execution, effectiveness, and turnover is this fact (Macey and Schneider, 2008; Sundari et al., 2024; Arora and Damarla, 2025). AI adoption directly influences this psychological state by redefining employees' demands and resources at hand (Makarius et al., 2020; Chuang et al., 2025).

4.1 The Job Demands-Resources (JD-R) Model

The JD-R model (Demerouti et al., 2001; Bakker and Demerouti, 2007) is the most fundamental conceptual framework for dual influence of AI study (Chuang et al., 2025). The theory puts forward that two psychological processes occur at the same time:

- a. **Motivational Process:** Job Resources which help to increase engagement, by having positive effects on productivity and job satisfaction (Bakker and Demerouti, 2007; Lesener et al., 2020).
- b. **Health Impairment Process:** Current job demands drain out energy which leads to exhaustion, and in the long run this negatively impacts well-being and work performance (Bakker and Demerouti, 2007; Gerdiken et al., 2021).

4.1.1 AI as a Job Resource: Driving Engagement

Looking at AI adoption, some features of the technology play the role of job resources to help increase the motivational process. (Chuang et al., 2025; Makarius et al., 2020; Prentice et al., 2023).

- **AI Efficacy:** The perceived usefulness and reliability of the AI system are considered its key strengths (Chuang et al., 2025; Davis, 1989, as cited in Aramali et al., 2025). The higher the effectiveness of the AI, the lesser the mental effort and time-related stress; this, in turn, enhances employee engagement and overall job satisfaction (Chuang et al., 2025).
- **Adoption of Generative AI:** Especially, GenAI has been viewed as an enhancer to many, quite rightly (Chuang et al., 2025). By generating new content and pointing out patterns in a way that can be both surprising and revealing, GenAI systems are believed to assist employees in improving their performance and provide better amounts of positive engagement (Chuang et al., 2025; Prentice et al., 2023).
- **Engagement as a Mediator:** Employee engagement conceptually has played the role of a

mediator in translating the positive effect of AI effectiveness and GenAI uptake on essential work outcomes, productivity enhancement, and job satisfaction (Chuang et al., 2025; Prentice et al., 2023).

4.1.2 AI as a Job Demand: Inducing Technostress

It is to be noted that AI has led to change in job requirements that has led to depletion of employee resources and has also affected the health adversely (Chuang et al., 2025).

- One major challenge employees face is **AI-related technostress**. This stress comes from constantly having to keep up with new technologies, worrying about job security, and struggling to maintain work-life balance as technology increasingly invades personal time (Chuang et al., 2025; Gerdiken et al., 2021; Koo et al., 2021). According to Chuang et al. (2025), technostress reduces job satisfaction and leads to increase in fatigue.
- **Negative Effects of technostress:** Since technostress has been considered as a reason for burnout, it leads to increase in work-family conflict and may lead to lower job satisfaction (Chuang et al., 2025; Gerdiken et al., 2021). For employees who have been in the organization for long duration, they may experience higher levels of technostress due to their lower ability to adapt to new methods of work (Chuang et al., 2025; Hinge et al., 2023a).
- **The Paradox:** There might be gain in productivity but it may come along with technological stress brought on by AI (Chuang et al., 2025; Tarafdar et al., 2007). The paradox emphasizes the necessity of the JD-R model, which considers both the strain route (AI as demand) and the motivational route (AI as resource) in order to communicate the contradictory but subtle evidence of AI adoption (Chuang et al., 2025).

4.2 The Role of Psychological Factors

Emotional and psychological contemplation have a strong effect on motivation in AI settings, which is in line with Self-Determination Theory (SDT) which connects autonomy and competence with psychological health (Deci and Ryan, 2000, cited by Gómez Gandía et al., 2025).

- **Perceived Individual Benefits (PiB):** In SME environments, the degree to which AI implementation is seen to produce individual benefits (PiB) (such as improved efficiency or prestige) determines Employee Smart Experience (ESE) strongly (Noerman et al., 2025). It, in turn, has a major impact on the employee's continuance intention to utilize (CIU) AI in HRM, ensuring long-term commitment (Noerman et al., 2025).

- **Hedonic Motivation (HM):** Hedonic motivation, characterized by the enjoyable features of technology utilization, positively affects both perceived effort expectancy (Pee) and PiB (Noerman et al., 2025). Making AI tools enjoyable and simple to use (i.e., resolving HM) directly leads to positive experience and prolonged persistence (Noerman et al., 2025; Vijai, 2023).
- **Work-Life Balance:** AI applications can promote work-life balance by pre-automating working hours, avoiding burnout, and delivering timely wellness tips, thus enhancing engagement (Katam, 2024; Liu et al., 2019; Sundari et al., 2024; Zheng et al., 2016).

5. AI AS A STRATEGIC RESOURCE: AUGMENTING ENGAGEMENT MECHANISMS

AI makes it easier to shift Human Resource activities from administration-focused to strategic ones through automation of standard procedures and support for personalized, data-driven engagement programs (Arora and Damarla, 2025; Dinesh Kannaa and Karthika, 2024; Sundari et al., 2024).

5.1 Automated Repetitive Tasks for Strategic Priorities

The automation of repetitive and administrative work is the basis for how AI increases interaction, which corresponds to the wish of HR professionals for gaining a "seat at the table" (Weng and Aguinis, 2024).

- **Gains in Efficiency:** AI helps to automate a lot of labour-intensive tasks like data analysis, scheduling, payroll processing, and the first level of recruitment screening (Dinesh Kannaa and Karthika, 2024; Mutsuddi et al., n.d.; Sundari et al., 2024). The automaton in turn helps to increase operational efficiency and enables the HR teams to channelise their attention to higher-level, strategic problems such as development of talent, creation of pathways to improve culture, and direct employee relationship management (Sundari et al., 2024; Weng and Aguinis, 2024).
- **Reduction in Burnout:** By reducing monotonous activities and improving effectiveness, AI applications can help in reducing burnout in job for HR professionals themselves so they can invest more time and energy to take care of complex strategic questions and one-on-one employee assistance, which leads to a direct positive impact on employee engagement (Weng and Aguinis, 2024; Zielinski, 2023, as cited in Weng and Aguinis, 2024).
- **Resolving Complex Tasks:** Generative AI (GenAI) acts as a valuable partner for HR professionals, facilitating them in managing complex tasks such as creating recruitment strategies that are in sync with the company's culture or helping them design effective

performance evaluation systems (Weng & Aguinis, 2024). This kind of *Human-AI collaboration* focuses on enhancing human judgment and decision-making rather than replacing it (Wilson & Daugherty, 2018, as cited in Weng & Aguinis, 2024; Zhang & Chen, 2019, as cited in Gómez Gandía et al., 2025).

5.2 Personalized Employee Experience and Retention

AI helps in creating highly personalized experience for employees, which becomes key to Employee Experience (EX) in today's world, which looks at employee journey as a whole (Morgan, 2017, as cited in Noerman et al., 2025; Shrestha and Bohr, 2024).

- a. **Personalized Support and Communication:** Generative AI-powered chatbots and virtual assistants use natural language processing (NLP) to provide real-time, personalized support — helping employees with complex questions and offering information that fits their specific needs (Arora & Damarla, 2025; Pillai et al., 2023, as cited in Noerman et al., 2025; Weng & Aguinis, 2024). These regular, customized interactions make employees feel more valued and supported (Sundari et al., 2024). For instance, IBM uses its *Watson Recruitment Assistant*, and Unilever uses similar AI chatbots to improve the candidate experience and simplify tasks like interview scheduling (Weng & Aguinis, 2024; Unilever, 2023, as cited in Dabral, 2024).
- b. **Predicting the Attrition and taking steps to arrest the same:** AI-powered data analytics decipher a lot of information like performance reviews, workplace interactions, and work habits to predict a set of employees who might be at risk of attriting or showing early signs of burnout or disengagement (Arora & Damarla, 2025; Fitzgerald, 2018, as cited in Vijai, 2023; Shinde, 2025a; Sundari et al., 2024). The organizations could use these insights for proactive measures to take care of their people, evolving from a reactive to proactive approach by anticipating and dealing with issues early (Shinde, 2025a; Bositkhanova & Dadaboyev, 2025). Individualized interventions, like targeted recognition or tailored career plans, may then be aimed at high-risk employees, thus enhancing retention and allegiance (Arora and Damarla, 2025; Pangarkar et al., 2023, cited in P. Smita et al., 2023; Walford-Wright and Scott-Jackson, 2018, cited in Singh and Padhi, 2025). Integration of AI into workforce planning has proved to lead to reduced turnover rates and improved commitment in implementing organizations (Bositkhanova and Dadaboyev, 2025).
- c. **Ongoing Performance Feedback:** AI facilitates ongoing performance management through the collection and aggregation of various streams of data (Dinesh Kannaa and Karthika, 2024; Sundari

et al., 2024; Weng and Aguinis, 2024). Ongoing, real-time feedback, in contrast to the annual reviews characteristic of the past, offers employees timely, context-relevant direction, fostering competence and confidence development as well as competence and recognition feelings, all of which are critical for engagement (Dinesh Kannaa and Karthika, 2024; Krupp and Meyer, 2018, as cited in Vijai, 2023).

5.3 AI in Learning and Development

Generative AI can help in customizing Learning and Development for employees which in turn affects their engagement in the long run, leading up to the motivational effect of competence development (Arora and Damarla, 2025; Mutsuddi et al., n.d.).

- **Personalized Learning Paths:** AI can help identify what skills employees need to develop based on what their career goals are, then customize the learning material, pace, difficulty level, and format to meet each person's needs (Arora and Damarla, 2025; Weng and Aguinis, 2024; Kaur and Singh, 2020, as cited in Vijai, 2023). This type of personalized learning plan allows for more effective training to take place, and it also increases the employees' motivation and overall satisfaction (Arora and Damarla, 2025; Boudarbat and Montmarquette, 2023).
- **Immersive Training:** AI helps build virtual training spaces that mirror real-life work situations, giving employees a chance to practice and learn through experience. This hands-on approach makes learning more engaging and keeps employees motivated (Arora and Damarla, 2025).

6. THE SHADOW OF AUTOMATION: CHALLENGES TO WELL-BEING AND TRUST

AI provides great opportunities for better interaction, but, it also comes with certain pressures, risks, and ethical concerns that can impact employees' mental health, trust, and long-term loyalty (Arora and Damarla, 2025; Chuang et al., 2025; Úbeda-García et al., 2025).

6.1 Psychological Demands and Job Insecurity

AI technostress is a universal work requirement which leads to burnout and adversely affects employee well-being (Chuang et al., 2025).

- **Technostress and Burnout:** Technostress is increased when employees experience technological complexity in their work and ambiguity in the work environment (Chuang et al., 2025; Xia, 2023). The burnout results from the demand of physical, emotional, and cognitive requirements which negatively impacts the role of AI adoption and job satisfaction (Chuang et al., 2025; Gerdiken et al., 2021).
- **Work-Family Conflict:** AI-powered cloud systems and constant connectivity often blur the

boundaries between work and personal life, causing more stress and conflict between professional and family responsibilities (Chuang et al., 2025; Gadeyne et al., 2018, as cited in Chuang et al., 2025). Researchers are now studying the emerging problem of adopting AI through the JD-R framework (Chuang et al., 2025).

- **Scepticism and Job Security:** Employees in various organizations seem to have a lot of scepticism towards adoption of AI in their respective organizations (When a project management survey was conducted, 74% of respondents reported to have mixed or negative feelings), job security was highlighted as the top concern (Aramali et al., 2025). Job insecurity leads to apprehension, fear, and insecurity, which leads to decrease in job satisfaction and involvement (Chuang et al., 2025; Koo et al., 2021; Pan and Froese, 2023). To make AI adoption work in the long run, it's important to overcome employee resistance and help them see AI as a supportive partner, not something to fear or compete with (Aramali et al., 2025; Wassan et al., 2021).

6.2 Ethical Dilemmas: Bias, Privacy, and Transparency

Ethical governance plays a crucial role because organizational trust—a key driver of employee engagement (Malla and Malla, 2023)—can quickly weaken when AI systems and their algorithms lack transparency (Úbeda-García et al., 2025; Yanamala, 2023).

6.2.1 Algorithmic Bias and Fairness

Machine learning models which have been derived from past data can sometimes carry forward and even worsen existing human biases, leading to unfair decisions in talent management. (Arora and Damarla, 2025; Bogen and Rieke, 2018, as cited in Vijai, 2023; Chen, 2023).

- **Recorded Bias:** There are some well-known examples which highlight the risks, like Amazon discontinuing an AI hiring software due to gender bias against women (Dastin, 2018, as cited in Vijai, 2023).
- **Mitigation Requirement:** There is established research on algorithmic bias in the workplace (Albaroudi et al., 2024). Adoption of AI requires a robust ethical system, due diligence, and caution to decipher biases in algorithmic decision-making so that we can come up with outcomes which are fair and equitable, (Arora and Damarla, 2025; Danner et al., 2023).

6.2.2 Data Privacy and Transparency

Tailoring participation to individual employees involves using a lot of personal data, which in turn leads to concerns around security and confidentiality about how that information is handled. (Arora and

Damarla, 2025; Colquitt et al., 2019; Úbeda-García et al., 2025).

- **Privacy Management:** Based on ideas like Privacy by Design (Cavoukian, 2010, as cited in Vijai, 2023; Kumar et al., 2021, as cited in Vijai, 2023; Yanamala, 2023), organizations need to put in place strong safeguards—such as encryption—and be open and transparent about how they protect employee data.
- **Reliability (explainability):** People tend to trust AI systems when they seem predictable, easy to understand, and reliable (Ala-Luopa et al., 2024; Balasubramaniam et al., 2023; Mirtaheri et al., 2026). However, this trust often falters because advanced AI models are complex and operate in ways that aren't always transparent (Glikson and Woolley, 2020; Úbeda-García et al., 2025).

6.3 Measuring Engagement through AI

In the recent past, Sentiment analysis (SA) and other similar AI tools have been used quite frequently to measure engagement metrics (Ali and Somu, 2023; Nayak, 2024).

- **Sentiment Analysis Frameworks:** SA frameworks have been used to analyse unstructured employee feedback, including those from surveys, emails, and open-ended remarks, to measure their attitudes towards the organization (Ali and Somu, 2023; Hinge et al., 2023b). This specific approach helps to come up with a real-time tracking feature which was not available in previous methods (Burnett and Lisk, 2019).
- **The Five 'V' Elements:** A very commonly used SA framework looks to measure employee engagement by using the five 'V' elements, to monitor and analyse the sentiment of employees effectively (Ali and Somu, 2023). The framework looks at major points to be considered to make the analytical output robust. In this framework *volume* requires large data volumes to provide for comparative sentiment patterns, *variety* refers to the different types of text, emojis, transcripts, and behavioural logs that helps to interpret context in a better manner. *Velocity* looks at the speed of generation and processing of the sentiment data to make useful insights and interventions. The feature of *veracity* looks to address accuracy of the model, its credibility and buffers sarcasm, cultural subtleties, and domain-specific terms. Ultimately *value*, describes the meaningful, actionable understanding gained from sentiment analytics to facilitate organizations in making decisions and also in performance.
- **Limitations in measurement:** Sentiment analysis (SA) processes are quite helpful in measuring engagement, but they have some limitations like ensuring accuracy, filtering out irrelevant data, and handling the subtleties of human language (Raghunathan and

Saravanakumar, 2023). Over and above this, knowledge of concepts of machine learning is limited among a lot of HR professionals, which makes it difficult in the effective development and application of these tools (Dabral, 2024; Úbeda-García et al., 2025).

7. SYNTHESIS, IMPLICATIONS AND FUTURE RESEARCH

7.1 Synthesis: The Human-Centric AI Paradigm

Studies have helped to reach a conclusion that for AI needs to be integrated in a way that it caters to people needs for it to be effective (Makarius et al., 2020; Weng and Aguinis, 2024; Toxtli, 2024). This approach finally helps to reach a deduction that AI not helps to increase efficiency, but also helps to interrelate with people, thereby influencing the way employees behave and influence the overall culture of an organization (Gómez Gandía et al., 2025; Makarius et al., 2020).

Adopting AI has transformed HR roles to be strategic (Sundari et al., 2024), significant progress in predictive analytics (Shinde, 2025), and facilitating well-being of employees by using tools such as personalized assistance (Chuang et al., 2025). Good governance, however, is the key to maximise the benefits. The relationship between AI and engagement is influenced by some important factors

- a. **Trust and Transparency:** Engagement of employees is built on the foundation of trust, which in turn is affected by algorithmic fairness, openness, and stringent data privacy policies (Arora and Damarla, 2025; Úbeda-García et al., 2025).
- b. **Leadership and Culture:** Organizations should have leaders who bring in both ethical values with emotional intelligence in their decisions towards digital transformation can help convert technological potential into people-centric results (Gómez Gandía et al., 2025; Wang et al., 2024). Response of employees to AI also depends largely on the culture of the organization (Gómez Gandía et al., 2025).
- c. **Psychological Mitigation:** Chuang et al. (2025) have highlighted that, Generative AI, in particular, can help ease out the negative impacts of technostress. Mental and emotional stress of employees can be reduced if organizations use tools which are easier to use and implement. (Bastida et al., 2025).

7.2 Managerial Implications: A Roadmap for Human-Centric AI

Professionals from HR domain can become the facilitators of AI-enabled workplaces (Bastida et al., 2025; Tursunbayeva, 2024). Organizations need to come up with an approach which strikes the right balance between technological efficiency and people-oriented management to maximise the effectiveness of AI (Bastida et al., 2025).

- a. **Investing on Upskilling/Reskilling:** To successfully integrate AI, organizations need people with expertise in areas like data science and computational linguistics (Arora and Damarla, 2025; Dabral, 2024). Preparing employees to work alongside intelligent systems also means having a strong focus on learning and development programs that focus on broad, transferable skills, AI awareness, and practical, on-the-job training (Bastida et al., 2025; Obi et al., 2025; Weng and Aguinis, 2024).
- b. **Encourage Trust through Transparency:** Organizations should build structures and ethical practices that promote openness about how AI systems work, especially when they're used to make decisions (Arora and Damarla, 2025; Gómez Gandía et al., 2025). This means setting clear guidelines for AI use and avoiding situations where too much automation takes control away from people (Bainbridge, 1983, as cited in Makarius et al., 2020).
- c. **Apply AI for Well-being of Employees:** Organizations could use predictive analytics to detect signs of disengagement amongst employees and accordingly respond with personalized actions—like wellness initiatives or personalized learning and development programs (Sundari et al., 2024). They should also focus on adopting Generative AI tools that genuinely make work easier, helping to reduce technostress and support a better work-life balance (Chuang et al., 2025).
- d. **Be prepared for Stringent Verification:** Because Generative AI can occasionally produce misleading or incorrect information, HR professionals using it should take extra care to verify its output. This means checking that any quotes or data come from reliable sources and comparing AI-generated insights with trusted HR best practices (Weng and Aguinis, 2024).

7.3 Limitations and Directions for Future Research

This literature review is limited by the fact that much of the existing research focuses more on concepts, with not enough empirical evidence available from different contexts. (Bositkhanova and Dadaboyev, 2025; Úbeda-García et al., 2025).

- a. **Longitudinal Empirical Studies:** To decipher why employee engagement looks at declining over time as AI use increases, future studies should use longitudinal research designs that track psychological factors (JD-R elements) and engagement levels before and after AI is introduced (Chuang et al., 2025).
- b. **Cross-Cultural and Cross-Industry Validation:** To understand if the JD-R findings on AI effectiveness, technostress, and the stress-reducing impact of Generative AI can be applied more widely, future studies should test these

models in varied organizations and cultural settings (Chuang et al., 2025; Úbeda-García et al., 2025; Bastida et al., 2025).

- c. **Human-AI Team Dynamics Impact:** Future research on human-machine collaboration should look at aspects other than individual experiences and examine how AI affects various aspects within teams like team dynamics, communication within the team, and the overall sense of psychological safety within teams (Arslan et al., 2021; Gómez Gandía et al., 2025).
- d. **Measuring Return on Engagement (ROE):** Future research should provide evidence from real-world of the financial and operational benefits that come from AI-supported employee engagement—such as the return on human capital investments (Dadd and Hinton, n.d.)—and clearly show how these benefits translate into better overall business performance (Bositkhanova and Dadaboyev, 2025; Úbeda-García et al., 2025).

8. REFERENCES

1. Albaroudi, E., Mansouri, T., and Alameer, A. (2024). A comprehensive review of AI techniques for addressing algorithmic bias in job hiring. *AI (Basel, Switzerland)*, 5(1). <https://doi.org/10.3390/ai5010019>
2. Ala-Luopa, S., Olsson, T., Väänänen, K., Hartikainen, M., and Makkonen, J. (2024). Trusting intelligent automation in expert work: Accounting practitioners' experiences and perceptions. *Computer Supported Cooperative Work*, 33(4). <https://doi.org/10.1007/s10606-024-09499-6>
3. Ali, N. A., and Somu, S. (2023). Revolutionizing employee engagement measurement: A sentiment analysis framework based on the five 'V' elements. In S. Sarma, S. Narang, and K. Prity (Eds.), *The adoption and effect of artificial intelligence on human resources management, Part A*. Emerald Publishing Limited.
4. Ammirato, S., Felicetti, A. M., Troise, C., and Corvello, V. (2024). Human resources well-being in innovative start-ups: Insights from a systematic review of the literature. *Journal of Innovation and Knowledge*, 9(4). <https://doi.org/10.1016/j.jik.2024.100580>
5. Aramali, V., Cho, N., Pande, F., Al-Mhdawi, M. K. S., Ojiako, U., and Qazi, A. (2025). Generative AI in project management: Impacts on corporate values, employee perceptions, and organizational practices. *Project Leadership and Society*. <https://doi.org/10.1016/j.plas.2025.100191>
6. Arora, R., and Damarla, R. B. (2025). A review on generative AI powered talent management, employee engagement and retention strategies: Applications, benefits, and challenges. *Procedia Computer Science*. <https://doi.org/10.1016/j.procs.2025.03.247>
7. Arslan, A., Cooper, C., Khan, Z., Golgeci, I., and Ali, I. (2021). Artificial intelligence and human workers interaction at team level: A conceptual assessment of the challenges and potential HRM strategies. *International Journal of Manpower*. <https://doi.org/10.1108/IJM-01-2021-0052>
8. Bakker, A. B., and Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology*. <https://doi.org/10.1108/02683940710733115>
9. Balasubramaniam, N., Krivtsova, E., Lwakatare, L. E., Munezero, M., and Al-Hamadi, H. (2023). Transparency and explainability of AI systems: From ethical guidelines to requirements. *Information and Software Technology*. <https://doi.org/10.1016/j.infsof.2023.107197>
10. Bastida, M., Vaquero García, A., Vazquez Taín, M. Á., and Del Río Araujo, M. (2025). From automation to augmentation: Human resource's journey with artificial intelligence. *Journal of Industrial Information Integration*. <https://doi.org/10.1016/j.jii.2024.100872>
11. Bositkhanova, N., and Dadaboyev, S. M. U. (2025). The utilization of AI in workforce planning: A systematic literature review. *Discover Global Society*. <https://doi.org/10.1007/s44282-025-00252-y>
12. Boudarbat, B., and Montmarquette, C. (2023). AI and employee development: Transforming learning and career planning. *Journal of Career Assessment*.
13. Burnett, J. R., and Lisk, T. C. (2019). The future of employee engagement: Real-time monitoring and digital tools for engaging a workforce. *International Studies of Management and Organization*. <https://doi.org/10.1080/00208825.2019.1565097>
14. Chuang, Y.-T., Chiang, H.-L., and Lin, A.-P. (2025). Insights from the Job Demands-Resources Model: AI's dual impact on employees' work and life well-being. *International Journal of Information Management*. <https://doi.org/10.1016/j.ijinfomgt.2025.102887>
15. Dadd, D., and Hinton, M. (n.d.). Performance measurement and evaluation: Applying return on investment (ROI) to human capital investments.
16. Danner, M., Hadžić, B., Weber, T., Zhu, X., and Rättsch, M. (2023). Towards equitable AI in HR: Designing a fair, reliable, and transparent human resource management application. In *International Conference on Deep Learning Theory and Applications*. Springer.
17. Dinesh Kannaa, K. V., and Karthika, S. (2024). AI and automation in human resources. *International Journal of Research in Human Resource Management*. <https://doi.org/10.33545/26633213.2024.v6.i2.e.244>

18. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., and Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*. <https://doi.org/10.1016/j.jbusres.2021.04.070>
19. Garg, R., Kiwelekar, A. W., Netak, L. D., and Ghodake, A. (2021). i-Pulse: A NLP based novel approach for employee engagement in logistics organization. *International Journal of Information Management Data Insights*. <https://doi.org/10.1016/j.jjime.2021.100011>
20. Gerdiken, E., Reinwald, M., and Kunze, F. (2021). Outcomes of technostress at work: A meta-analysis. *Academy of Management Proceedings*, 2021(1). <https://doi.org/10.5465/ambpp.2021.11807abstract>
21. Glikson, E., and Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*. <https://doi.org/10.5465/annals.2018.0057>
22. Gómez Gandía, J. A., de Lucas Ancillo, A., and del Val Núñez, M. T. (2025). Knowledge and artificial intelligence on employee behaviour advancing safe and respectful workplace. *Journal of Innovation and Knowledge*. <https://doi.org/10.1016/j.jik.2024.100750>
23. Hariri, W. (2023). *Unlocking the potential of ChatGPT: A comprehensive exploration of its applications, advantages, limitations, and future directions in natural language processing*. arXiv. <http://arxiv.org/abs/2304.02017>
24. Hinge, P., Thakur, A., and Salunkhe, H. (2023). Analysis of human resources attrition: A thematic and sentiment analysis approach. *Applications of Machine Intelligence and Data Analytics*. https://doi.org/10.2991/978-94-6463-136-4_72
25. Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. *Academy of Management Journal*. <https://doi.org/10.2307/256287>
26. Katam, R. (2024). Data + AI driven solutions for enhancing employee wellbeing and work-life balance. *International Journal of Scientific Research in Engineering and Management*, 8.
27. Koo, B., Curtis, C., and Ryan, B. (2021). Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *International Journal of Hospitality Management*. <https://doi.org/10.1016/j.ijhm.2020.102763>
28. Krakowski, S. (2025). Human-AI agency in the age of generative AI. *Information and Organization*. <https://doi.org/10.1016/j.infoandorg.2025.100560>
29. Malik, A., Budhwar, P., Mohan, H., and NR, S. (2023). Employee experience—the missing link for engaging employees: Insights from an MNE's AI-based HR ecosystem. *Human Resource Management*. <https://doi.org/10.1002/hrm.22133>
30. Marr, B. (2023). *The future of work: How AI and technology are shaping the workplace*. Forbes.
31. Mer, A., and Srivastava, A. (2023). Employee engagement in the new normal: Artificial intelligence as a buzzword or a game changer? In P. Tyagi, N. Chilamkurti, S. Grima, K. Sood, and B. Balusamy (Eds.), *The adoption and effect of artificial intelligence on human resources management, Part A*. Emerald Publishing Limited. <https://doi.org/10.1108/978-1-80382-027-920231002>
32. Mirtaheri, S. L., Movahed, N., Shahbazian, R., Pascucci, V., and Pugliese, A. (2026). Cybersecurity in the age of generative AI: A systematic taxonomy of AI-powered vulnerability assessment and risk management. *Future Generation Computer Systems*. <https://doi.org/10.1016/j.future.2025.108107>
33. Nayak, R. L. (2024). Navigating the AI revolution in HRM: A sentiment analysis perspective. *Educational Administration: Theory and Practice*.
34. Noerman, T., Riyadi, E. S., Yuliaji, E. S., and Natasha, C. A. M. (2025). The impacts of social influence and hedonic motivation on experience and continuance intention of using AI in SMEs' HRM. *Cogent Business and Management*. <https://doi.org/10.1080/23311975.2025.2542422>
35. Obi, L. I., Osuizugbo, I. C., and Awuzie, B. O. (2025). Closing the artificial intelligence skills gap in construction: Competency insights from a systematic review. *Results in Engineering*. <https://doi.org/10.1016/j.rineng.2025.106406>
36. Ossianilsson, E., Altinay, F., Shadiev, R., Benachour, P., Berigel, M., Dagli, G., Ayaz, A., Yikici, B., and Altinay, Z. (2024). Exploring the intersection of artificial intelligence and human resource management: A bibliometric study. *Broad Research in Artificial Intelligence and Neuroscience*.
37. Pan, Y., and Froese, F. J. (2023). An interdisciplinary review of AI and HRM: Challenges and future directions. *Human Resource Management Review*. <https://doi.org/10.1016/j.hrmr.2022.100924>
38. Prentice, C., Wong, I. A., and Lin, Z. (2023). Artificial intelligence as a boundary-crossing object for employee engagement and performance. *Journal of Retailing and Consumer Services*. <https://doi.org/10.1016/j.jretconser.2023.103376>
39. Rahim, S., Sahar, G., Jabeen, G., Khatoon, S., and Angaiz, D. (2025). Harnessing generative AI: Reviewing applications, challenges, and solutions for out-of-school children in developing regions. *Sustainable Futures*. <https://doi.org/10.1016/j.sft.2025.101206>
40. Raghunathan, N., and Saravanakumar, K. (2023). Challenges and issues in sentiment analysis: A

- comprehensive survey. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2023.3293041>
41. Schaufeli, W. B., Bakker, A. B., and Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement*. <https://doi.org/10.1177/0013164405282471>
42. Schaufeli, W. B., Salanova, M., González-Romá, V., and Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*. <https://doi.org/10.1023/a:1015630930326>
43. Shinde, S. (2025). Predictive HR analytics and employee attrition modelling: A strategic approach to workforce retention in the Indian context. *RESEARCH REVIEW International Journal of Multidisciplinary*. <https://doi.org/10.31305/rrijm.2025.v10.n6.022>
44. Shrestha, Y., and Bohr, J. (2024). Enhancing employee experience with AI: Innovations and impacts. *Journal of Organizational Behaviour*.
45. Sigfrids, A., D'Adda, A., Salini, S., and Oltramari, A. (2023). Human-centricity in AI governance: A systemic approach. *Frontiers in Artificial Intelligence*, 6. <https://doi.org/10.3389/frai.2023.976887>
46. Singh, A. P., and Padhi, A. (2025). "Impact of AI and automation on talent acquisition and employee retention." *International Journal of Research Publication and Reviews*.
47. Sundari, S., Silalahi, V. A. J. M., Wardani, F. P., Siahaan, R. S., Sacha, S., Krismayanti, Y., and Anjarsari, N. (2024). Artificial Intelligence (AI) and automation in human resources: Shifting the focus from routine tasks to strategic initiatives for improved employee engagement. *East Asian Journal of Multidisciplinary Research (EAJMR)*. <https://doi.org/10.55927/eajmr.v3i10.11758>
48. Tambe, P., Cappelli, P., and Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*. <https://doi.org/10.1177/0008125619867910>
49. Tursunbayeva, A. (2024). Artificial intelligence and human resource management. *Augmenting human resource management with artificial intelligence: Towards an inclusive, sustainable, and responsible future*. Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-75266-7_1
50. Úbeda-García, M., Marco-Lajara, B., Zaragoza-Sáez, P. C., and Poveda-Pareja, E. (2025). Artificial intelligence, knowledge and human resource management: A systematic literature review of theoretical tensions and strategic implications. *Journal of Innovation and Knowledge*. <https://doi.org/10.1016/j.jik.2024.100809>
51. Vijai, C. (2023). Artificial intelligence in HR employee experience: Personalization and engagement. In S. Sarma, S. Narang, and K. Prity (Eds.), *AI and innovation in HRM: The future of strategic HR in the service economy*. (Original work published in *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part A*).
52. Virmani, N., Sharma, S., Kumar, P., Luthra, S., Jain, V., and Jagtap, S. (2025). Navigating the landscape through digital human resource management: An initiative to achieve sustainable practices. *Sustainable Production and Consumption*. <https://doi.org/10.1016/j.spc.2024.100621>
53. Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., and Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management*. <https://doi.org/10.1080/09585192.2020.1871398>
54. Wang, G., Mansor, Z. D., and Leong, Y. C. (2024). Linking digital leadership and employee digital performance in SMEs in China: The chain-mediating role of high-involvement human resource management practice and employee dynamic capability. *Heliyon*. <https://doi.org/10.1016/j.heliyon.2024.e36026>
55. Wang, H., Dang, A., Wu, Z., and Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. *Computers and Education: Artificial Intelligence*. <https://doi.org/10.1016/j.caeai.2024.100326>
56. Wassan, S., Ali, Z., and Wassan, S. A. (2021). How artificial intelligence transforms the experience of employees. *Türk Bilgisayar Ve Matematik Eğitimi Dergisi*. <https://doi.org/10.17762/turcomat.v12i10.5603>
57. Weng, J., and Aguinis, H. (2024). How to use generative AI as a human resource management assistant. *Organizational Dynamics*. <https://doi.org/10.1016/j.orgdyn.2024.101029>
58. Xiao, J., and Yanghong, H. (2024). Architecting the future: Exploring the synergy of AI-driven sustainable HRM, conscientiousness, and employee engagement. *Discover Sustainability*.
59. Yanamala, K. K. R. (2023). Transparency, privacy, and accountability in AI-enhanced HR processes. *Journal of Advanced Computing Systems*.