International Journal of Applied Mathematics

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

USING ARTIFICIAL INTELLIGENCE FOR PROACTIVE TALENT RETENTION: PREDICTING BURNOUT AND JOB ABANDONMENT

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Abstract

In the post-pandemic workplace, employee turnover and burnout have emerged as critical challenges, driving organizations to seek innovative, proactive retention strategies. Here, the application of Artificial Intelligence (AI) in predicting employee burnout and the likelihood of job abandonment is examined, thus enabling early interventions to enhance talent retention. Recently, AI has become a powerful tool in predictive analysis. This study uses a focus group approach and explores how AI can be used to analyze workplace data to predict and flag employees who are at risk before their turnover intentions solidify. A focus group discussion was held using Human Resource (HR) managers and employees to gather insight on the perceived benefits, concerns and anticipated challenges for implementing an AI-based retention system. It was found that an AI-based system enhanced early burnout detection based on continuous monitoring of stress indicators and patterns of work. This allowed individualistic personalized intervention, such as personal wellness and workload adjustment, to reduce the turnover. The participants highlighted that, in any AI-based retention initiative, ethical considerations, transparency of AI algorithms, data privacy and the need for continuous human oversight were essential. This paper concentrates on group finding, drawing on literature on AI in Human Resource Management (HRM) and Employee Well-Being (EWB). The outcomes stated that the AI's success will depend on careful, human-centric implementation that addresses trust and ethical issues while offering significant potential to support proactive talent retention by predicting burnout and attrition risks. This study presents a framework for integrating AI into retention strategies. This study also offers practical recommendations for HR practitioners to leverage AI insights and foster EWB and loyalty.

Keywords: *Talent Retention; Artificial Intelligence; Burnout; Employee Turnover; Predictive Analytics; Human Resource Management; Ethical AI.*

1. Introduction

Employee Retention (ER) is crucial for an organization's success since high turnover can mitigate output and cause significant expenses (Al-Suraihi, et al, 2021). Businesses lose institutional knowledge and incur costs for hiring and training new employees. When talented employees leave, firms see a decline in team morale (Nyambok and Hongo, 2022). Employee burnout is a persistent condition characterized by physical and mental exhaustion. It has been widely recognized as a significant factor in employee turnover (Salama et al, 2022). Burned-out Employees have lower levels of commitment and job satisfaction. Such employees most

Received: August 06 2025

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

likely resign. In recent years, the rise in voluntary departures and reported burnout indicates the need for proactively introducing retention strategies.

Organizations essentially consider predictive analytics powered by AI as a way to address this issue (Prasad and Sumitra, 2025). Business entities can identify which employee are most likely to burn out or leave by Integrating Machine Learning (ML) algorithms in their HR operations. This enables them to take steps to minimize employee turnover proactively. As per the recent survey, AI software can identify early warning signals of stress or disengagement by analyzing workload, performance metrics, employee behaviour patterns and even well-being indicators. Many burnout indicators, such as email sentiments, work hours, feedback rating and project deadlines, can be easily monitored by an AI system before management becomes aware of the issue. By analyzing these indicators, firms can make individualized proactive interventions. For example, reallocating workload, providing help by a coach or other wellness tools, or providing financial or nonfinancial recognition and support. This may reduce burnout from intensifying and bring the employee back on track by capturing these indicators (Madanchian, 2024). By identifying issues early, reducing unnecessary turnover, improving EWB and fostering a healthier workforce, this forward-looking application of AI can potentially enhance retention results. Using AI for predictive retention helps ensure a supportive work culture that retains happy and productive employees in the long haul (Paigude et al, 2023). The effect of AI in talent retention is illustrated in Figure 1.

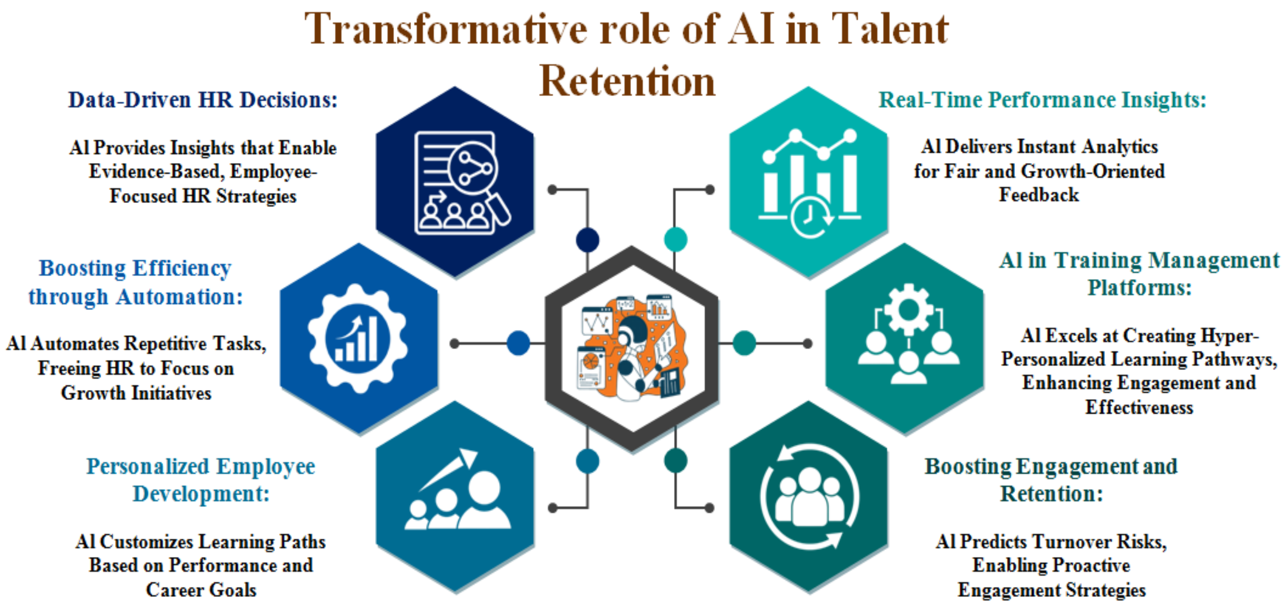

Figure 1: Impact of AI in modern talent retention

Source: Authors basis literature review

Nevertheless, it is challenging to make talent retention using AI. In this context, there have been ethical and practical issues about utilizing employee data and algorithms. If AI systems constantly monitor employees' work behaviour, they can feel that their privacy is being invaded

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

or watched (Sharma and Deouskar, 2024). There are also questions of fairness and transparency. HR professionals and employees must trust AI's burnout or turnover risk predictions. Black-box AI models lacking interpretability can undermine confidence in the system's recommendations and managers might hesitate to act on an algorithm's warning without understanding the rationale (Yu and Li, 2022). For establishing trust in these systems, guaranteeing transparency (such as via the employment of explainable AI methods in displaying which variables affected a prediction) is thus essential. If the AI is trained using past data that is reflective of past discrimination, there is also a possibility of algorithmic bias.

Stringent data governance, Employee Engagement (EE) and human supervision are essential before introducing AI in the HR function. This would avoid inaccurate or discriminatory predictions and ensure the technology is used responsibly and efficiently.

Problem Statement:

AI-based analytics can predict Employee burnout and attrition. However, most firms find implementing these technologies successfully in real-world business scenarios challenging. High Employee turnover is a matter of significant concern; it causes increased hiring costs, reduced productivity and lower morale among staff members. Rather than averting issues, traditional retention tactics usually address them after they have arisen (Inaganti et al, 2021 and Diaz et al, 2023). The use of AI in proactive retention is still relatively new and poorly understood. It is essential to investigate the organizational factors that affect the successful application of AI and how it can be utilized to forecast burnout and attrition risk more accurately.

Aim of the Study:

This study investigates how proactive talent retention can be enhanced using AI-based prediction algorithms to forecast employee burnout and job desertion risks. Its objectives are to assess how well AI can detect at-risk workers early on and determine how HR managers and employees perceive AI-driven retention tactics.

Objectives of the Study:

- To evaluate the current applications, benefits and challenges of using AI and ML in predicting employee turnover and burnout in HRM.
- To examine predictive analytics to detect patterns or indicators in employee behaviour and work conditions that signal elevated burnout or turnover risk.
- To scrutinize, through focus group discussions, the perspectives of HR professionals and employees on the usefulness and trustworthiness of AI-based tools for predicting burnout and attrition.
- To assess the role of human oversight, data transparency and ethical considerations in deploying AI for talent retention.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

- To develop recommendations for integrating AI-driven insights with HR interventions (such as wellness programs or managerial support) to mitigate burnout and enhance ER.

This paper is structured as follows: The second Section reviews the relevant literature on AI applications in ER and burnout prediction. The third presents the theoretical framework underpinning the research, drawing on the Job Demands-Resources model to conceptualize burnout within the context of AI-driven work environments. The fourth describes the research methodology, including the qualitative design, focus group procedures, data analysis approach and ethical considerations. The fifth presents the results and analysis of the focus group findings, integrating them with a discussion of their implications. Finally, the Sixth Section concludes the study, outlining its limitations and suggesting future scope.

2. Literature Review

Application of AI specifically in the area of human resources retention is a fairly new area and research is ongoing in this field. As we undertake the Literature Review, it is to be noted that due care has been taken to keep the Literature Review contemporary.

I AI Applications in Human Resource Management and Talent Retention

The integration of Artificial Intelligence (AI) into Human Resource Management (HRM) has revolutionized traditional employee engagement (EE) and retention (ER) practices for corporates. We are seeing increasing intersection of data-driven engagements and proactive decision-making. Recent research emphasizes the growing potential of AI-driven analytics, predictive modeling and automation in identifying turnover risks, enhancing employee satisfaction and optimizing organizational performance.

Basnet (2024) investigated the effect of AI-driven predictive analytics on ER strategies in HRM. To discover the application of AI and ML in HRM for improving ER, a qualitative research design utilizing case study analysis was employed in this study. Case studies of five firms—IBM, Deloitte, Kronos (UKG), Unilever, and Amazon—were investigated to understand how AI-driven predictive analytics were implemented and their effect on ER. The major key findings were the benefits of personalized involvement, the utilization of diverse data points, and the remarkable cost savings attained via AI-driven retention strategies.

Ranganath et al (2024) investigated the AI-facilitated EE approach to optimize productivity and augment firm retention rates. The approach aimed to personalize engagement strategies, detect key drivers of employee satisfaction, and identify potential turnover risks by leveraging AI technologies, like NLP, ML, and SA. The study adopted a mixed-methods research design that integrated quantitative and qualitative approaches to examine the effect of AI-facilitated EE approaches on productivity and retention in Telangana State manufacturing firms. A significant positive impact of AI-enabled EE approaches on productivity and retention within the manufacturing firms of Telangana State was revealed. Firms that implemented AI-driven tools and strategies faced enhancements in employee satisfaction, motivation and commitment, causing improved productivity levels. Despite the overall positive results, numerous challenges

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

and limitations related to implementing AI-facilitated EE approaches in manufacturing industries were detected. However, concerns about data privacy, algorithmic bias, skill gaps and resistance to change were included.

Yanamala (2024) aimed to analyze the incorporation of AI into talent retention and development frameworks, concentrating on predictive analytics, personalized learning, Sentiment Analysis (SA) and engagement tools. AI-driven models, like logistic regression, clustering algorithms and SA, were utilized to assess turnover risk, design customized development programs and augment EE. Simulated data from 1,000 employees demonstrated how these methodologies could detect at-risk employees, mitigate turnover and enhance engagement. As per the findings, AI-driven talent management strategies considerably improved retention, especially in high-turnover departments and created more personalized development opportunities for employees. Nevertheless, the simulated data's utilization restricted the generalizability of the outcomes to real-world firm contexts.

Hoa Do et al. (in 2025) evaluated how and when AI-driven HRM promoted employee resilience and adaptive performance. The model signified that the association betwixt AI-driven HRM and employee outcomes was mediated by employee exploration centered on self-determination theory. Two studies were carried out to test the hypotheses. In study 1, a 12-item AI-driven HRM scale across three samples, including 50 managers, 150 employees for Exploratory Factor Analysis (EFA) and 150 employees for Confirmatory Factor Analysis (CFA), was developed and validated. In study 2, data were gathered from 274 US employees via a 3-wave survey and the effect of AI-driven HRM on resilience and performance was also investigated. A salient boundary condition to reinforce the mediated associations betwixt AI-driven HRM and employee resilience and adaptive performance was the trust in AI. Nevertheless, numerous drawbacks were found in the study. Initially, from similar sources, the datasets were collected online. Secondly, the first to be investigated empirically was the AI-driven HRM. Therefore, other potential employees' results might be affected.

Pooja Sharma et al. (in 2025) explored the adoption and effect of HR Analytics and AI in the Information Technology (IT) sector. With 15 HR managers, the data were gathered via semi-structured interviews. The research design deployed was qualitative. As per the findings, HR Analytics and AI significantly affected capabilities, HR functions and decision-making in the IT field. The HR professionals possessed technical skills, like data analysis, coding, analytical thinking, design thinking and domain knowledge, to successfully adopt HR analytics and AI. The study was conducted only in the IT sector, whereas the same result did not apply to other industries.

Qin et al (2025) in their research presented a taxonomy of research efforts across talent management, organization management and labor market analysis. They provided a comprehensive survey of Artificial Intelligence (AI) technologies used for talent analytics within HRM. We find detailed descriptions of the background of talent analytics and categorization techniques of relevant data.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Triveni (2025) explored the transformative role of AI in improving EE and retention within HRM. It examined how AI-driven technologies, like predictive analytics, Natural Language Processing (NLP) and AI-powered platforms, were deployed. The study established how AI boosted engagement and retention via case studies across industries, thus nurturing a more buoyant and adaptive workforce.

II AI for Predicting and Preventing Burnout and Job Abandonment

Recent literature underscores the growing role of Artificial Intelligence (AI) in proactively working around employee burnout and improving workplace wellness. AI-driven systems and predictive models are increasingly being deployed to monitor work patterns, detect early signs of stress and support timely interventions that prevent employee disengagement and turnover.

Azlaan (2023) explained the potential of integrated AI systems for monitoring work patterns as a strategic approach to combat burnout. Organizations leveraging ML and data analytics have increased insights into employee workloads, engagement levels and other stress indicators. The study used a structured method for integrating these AI-driven systems into organizational practices, while creating a significantly helpful work environment. The study found that timely personalized interventions were made possible by the integrated AI approach used to combat burnout and it elaborated on the use of real-time data to monitor work patterns and promote work-life balance. AI enables companies to make informed decisions about workload management and EWB by continuously collecting and analyzing employee data, ultimately causing enhanced employee satisfaction and retention.

Liang (in 2024) emphasized these AI models' design, implementation and effectiveness, highlighting their potential to transform IT companies' management of employee health and productivity. AI models predicted potential burnout before it occurred by investigating the historical data, including work patterns, workload intensity, stress indicators and personal well-being metrics. These models utilized ML algorithms, namely decision trees, neural networks and support vector machines to detect significant factors contributing to burnout. Moreover, personalized interventions, like workload adjustments, breaks, or stress management resources, were offered by AI tools, thus tailoring to individual needs and preferences. Integrating such predictive models into workplace environments aimed to foster a proactive approach to EWB, enabling organizations to maintain a healthier workforce and reduce turnover.

Wilton et al. (2024) developed a predictive model of occupational burnout and estimated burnout-related costs utilizing consumer-grade wearable smartwatches and systems-level data. In 3 cohorts, 360 Registered Nurses (RNs) were employed. These cohorts would act as training, testing and validation datasets to develop predictive methodologies. As per the study, the Burnout Prediction Using Wearable and Artificial Intelligence (BROWNIE) was framed to be decentralized and asynchronous, minimizing any extra burden on RNs and ensuring that night shift RNs had equal access to investigation resources and procedures. Several drawbacks were found in the study. There was a probability that bias could be present in future prediction modeling due to the sampling limitations. Sampling was logistically limited to whole units,

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

even though system-level data were gathered at the unit level at the institution and did not encompass performance metrics of individual RNs. The sample was inherently not independent owing to this limitation.

Unguren et al. (2024) examined the association betwixt work stress, work-associated burnout and turnover intention. The mediating role of work-associated burnout and the moderating role of job security and financial dependence were also explored. Amongst 494 hotel employees in 5-star hotels in Belek and Manavgat, Türkiye, a cross-sectional survey was conducted using a moderated mediation research methodology. As per the study, work-related burnout was increased by work stress, thereby elevating turnover intention. Moreover, work-associated burnout mediated the relationship between work stress and turnover intention. Furthermore, the relationship betwixt work stress levels and work-related burnout was moderated by the perceived job security. This study employed a cross-sectional methodology due to the complications encountered during data collection. Nevertheless, the generalizability of findings might be affected.

Chheda et al (2025) investigated the effectiveness of AI-based tools on hiring time, enhancing job candidate fit and predicting attrition risk. AI-predicted attrition risk (APAR) was evaluated across 1000 resumes and over three years. It was found empirically that suitable AI tools usage could predict attrition. This could be very effective for HR managers to plan contingency plans keeping this metric in mind.

Madhumita et al (2025) observed that by integrating Artificial Intelligence in employee developments could positively affect retention. While one uses AI for ensuring a culture of regular learning and bridging skill gaps, it has effects on retention too.

III Ethical, Technical and Methodological Considerations in AI-Driven Talent Retention

AI-powered tools like predictive analytics, personalized learning programs and AI-driven communication platforms could enhance employee satisfaction and reduce turnover. However, it was necessary to ensure that AI Implementation is appropriately managed by addressing ethical concerns and that the technology is used to supplement human decisions. However, many challenges should be addressed, such as ethical concerns, data integration and employee trust. Effective retention strategies should be developed by tailoring AI tools to meet the firm’s needs, assimilating AI insights into human decision-making processes and safeguarding the ethical utilization of AI.

Paigude et al in 2023 observed that usage of AI in HR has raised many questions related to ethics especially in the area of biases and transparency. This is logical as AI models rely extensively on historical data, they may perpetuate and aggravate existing biases, leading to multiple issues. Additionally, the “black box” nature of many AI systems makes it difficult to understand or justify their decisions, posing risks in sensitive HR contexts. To address these challenges, the researchers suggest that companies should maintain transparency, use diverse training data, regularly audit algorithms for bias.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Majumder and Misra (in 2025) discussed the ethical considerations and future scopes of AI in EE. Moreover, the human-AI collaboration and empathy were addressed in the study. As per the study, balancing privacy and surveillance in AI monitoring systems was a critical consideration. To mitigate bias and ensure fair treatment of employees, firms must ensure transparency and credibility when utilizing AI and employee analytics. Furthermore, to maintain a healthy relationship betwixt people and computers, the development of AI systems that fostered employee trust as well as collaboration was necessary.

Meenu Chaudhary et al (in 2025) intended to analyze the transparency in predicting employee churn utilizing explainable AI. The model employed in this study aligned with the Knowledge Discovery in Databases (KDD) framework, an entrenched methodology for data mining. It was centered on the Cross-Industry Standard Procedure for Data Mining (CRISP-DM) approach. A dataset containing details of 1470 employees was utilized. This research used a predictive model to compare the top two benchmark algorithms centered on performance metrics. As per the outcomes, numerous features contributing to employee churn were ranked based on their significance and association with churn. The necessity of technical expertise for deriving the outcomes from the problem statement was the limitation of the Explainable AI (XAI) implementation.

3. Theoretical Framework

This research is based on the Job Demands-Resources (JD-R) model. This model is a well-established approach in organizational psychology that offers insight into understanding burnout and engagement. As per the JD-R methodology, job stress and ultimately burnout arise when job demands (aspects of a job that require sustained effort and incur psychological cost) chronically exceed the job resources (aspects that help reduce demands or stimulate personal growth) available to an employee. The JD-R lens is adopted to interpret how AI-driven management systems might influence EWB and retention. The technology can be viewed as both a potential demand and a resource in the context of AI integration.

An AI tool may require employees to learn new skills, complex software, algorithm-driven workflows and, in their daily tasks, higher degree monitoring and data analytics. Such AI-related technostress can heighten workloads or create uncertainty, thus contributing to burnout if not addressed (Meduri et al, 2024). Conversely, AI systems can act as job resources by automating tedious tasks, providing decision support and enabling more flexible work arrangements (Soori et al, 2024). AI has the potential to reduce employees' mental strain and free up time for more meaningful activities by offloading repetitive work and offering personalized recommendations. This, in turn, must alleviate burnout and enhance engagement theoretically.

The influence of AI on the JD-R balance relies on implementation factors. For example, the degree to which AI integration permeates an employee's workflow can have a paradoxical effect. If AI is employed to streamline work (e.g., handling low-value tasks) thoughtfully, it can mitigate job demands and prevent burnout (Balaguru et al, 2024). Suppose AI is introduced

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

without adequate support or is not aligned with employees' skills. In that case, it can erode their sense of control and create anxiety, which effectively becomes an additional demand that increases the risk of burnout (Golgeci, 2025). In this framework, employee training and self-efficacy emerge as crucial moderators. When employees are well-trained and confident in using AI systems, they perceive the technology more as a helpful resource than a threat, which can buffer the stress response.

By enhancing employees' feelings of competence and autonomy with the new tools, Sufficient training and change management convert AI from a demand into a resource (Kassa and Worku, 2025). Another factor is AI personalization. AI solutions tailored to individual work styles (for example, allowing employees to customize alert thresholds or recommendation types) are more likely to be embraced as supportive resources, thus mitigating cognitive load and burnout (Cao et al, 2025). Contrastingly, one-size-fits-all AI mandates may fail to meet diverse needs, causing poor performance as a resource.

Burnout plays a central role as a mediator betwixt job demands/resources and the outcome of turnover intention by applying the JD-R theory to talent retention Scholze and Hecker (2024). A core premise is that burnout is increased by elevated job demands (including those possibly introduced by AI, such as constant connectivity or performance surveillance) and higher burnout causes stronger intentions to quit. Conversely, enriching job resources (AI can contribute to, if appropriately used, e.g., by providing employees with more autonomy or support) should decrease burnout and enhance engagement, thus mitigating turnover intentions. In this study, the qualitative exploration examines these dynamics by eliciting participants' perceptions of how an AI-based burnout prediction system would alter their work demands or resources. For example, do employees see an AI monitoring tool as an intrusive demand (something extra to worry about) or a supportive resource (an assistant that might ease their workload)? The focus group findings will be interpreted through this theoretical lens, identifying whether the themes raised align with concerns of increased demands (privacy invasion, pressure always to be "optimizing" under AI's eye) or increased resources (feeling more supported and heard due to AI insights). The JD-R framework offers a basis for anticipating the conditions under which AI-driven talent retention efforts will likely succeed or fail (Kim and Kim, 2024). An AI system that is perceived to augment resources (through fairness, transparency and genuine relief of burdens) should theoretically improve well-being and retention. Contrastingly, suppose the system is rolled out to amplify demands (through mistrust, added stress, or role ambiguity). In that case, it can inadvertently contribute to burnout and turnover – the very outcomes it was meant to prevent. The study can better explain the nuanced opinions of the participants and formulate recommendations to ensure that AI functions as a beneficial resource in talent retention initiatives by keeping the balance of demands and resources in focus.

4. Research Methodology

4.1 Research Design

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

This study adopts a qualitative research design to understand perspectives on using AI for proactive talent retention. Given the exploratory nature of this inquiry, a qualitative approach is appropriate, addressing “how” and “why” questions about AI’s role in predicting burnout and turnover. A focus group discussion was then specially employed for the primary data collection method. Focus groups allow participants to interact and spark ideas with one another, which is valuable for uncovering shared concerns, divergent opinions and collective norms regarding a novel topic like AI-driven retention. The research is positioned within an interpretivist approach that aims to interpret the meanings and attitudes that HR professionals and employees attribute to the prospect of AI-based burnout prediction systems.

4.2 Participants and Procedure

In a large service-oriented organization, three focus group sessions have been conducted. This organization implements an AI-driven HR analytics tool for EWB. Each focus group comprises 6–8 participants, totaling 20 participants (11 female, 9 male). Two types of stakeholders are intentionally mixed in the sessions to capture various viewpoints: HR managers (responsible for overseeing retention and employee development programs) and non-managerial employees from multiple departments (who would be the subjects of any AI monitoring for burnout risk). This composition encourages dialogue between those who may implement the AI system and those who would be affected by it. The participants ' roles include HR business partners, team leaders, software engineers, customer support representatives and project managers. The participants aged about 20 to 50 years had experience ranging from 3 to 15 years. Thus, the group composition ensured a diverse range of ages and experiences. Before the discussions, participants are given a brief scenario outlining an assumed AI-driven “Employee Wellness Monitor” system. It was further explained that the system could analyze data, such as email/chat sentiment, working hours, task completion rates and time-off patterns and use the information to predict whether an employee is at risk of burnout or planning to quit. It also enlightens possible interventions (e.g., the system might alert HR to check in with the employee or recommend resources). In order to stimulate discussion and debate, this scenario serves as a common reference point. It also assures participants that no actual monitoring occurs during this study.

Each focus group is conducted in a conference room (via video conference for two remote participants) and lasts approximately 90 minutes. A trained moderator enables the sessions using a semi-structured discussion guide. Key questions comprised: “What are your initial reactions to the idea of an AI system monitoring burnout risk?”, “How might you respond if HR approached you based on an AI alert?”, “What benefits or opportunities do you see in using such a tool?” and “What concerns or challenges does this raise for you?”. Follow-up prompts probe specific areas like trust in the system’s accuracy, perceived intrusiveness, the kind of data considered sensitive and how participants felt management should act on AI insights. All members were encouraged to share their views without hesitation throughout the session. A note taker continuously recorded non-verbal cues and group dynamics.

4.3 Data Analysis

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

All focus group discussions are audio-recorded with consent and transcribed verbatim. Thematic analysis is also employed to analyze the qualitative data. The research team first individually reviews the transcripts to note initial impressions, following the six-step approach of familiarization, coding, theme development, review, definition and writing. Next, two researchers independently open-code the transcripts using qualitative data analysis software, assigning codes to segments of text that indicate distinct ideas (for example, codes like “privacy concerns,” “usefulness – early warning,” “manager trust in data,” “fear of surveillance,” “need for human touch,” etc.). The researchers then meet to compare and discuss these codes, resolving discrepancies via consensus and merging similar codes.

The codes are structured into broader themes and sub-themes via an iterative process. Privacy and Surveillance, Trust and Transparency, Usefulness of AI Insights, Human Oversight and Empathy and Implementation and Training are the major themes that emerged. Under each theme, sub-themes capture nuances (for instance, within Privacy concerns, sub-themes differentiate between data privacy vs. feeling psychologically “watched”). Thereafter, the themes are studied against the raw data to ensure an accurate reflection of the participants' voices and that no significant ideas are overlooked. Each theme is defined and given a narrative description to identify representative quotes. These quotes are then included in the findings to illustrate participants’ points vividly in their own words.

Investigator triangulation is used to enhance validity. The third researcher audits the coding and theme development process. There is a high degree of agreement on key themes and any minor differences in interpretation are discussed until alignment is achieved. Member checks are conducted in a follow-up step: a summary of the identified themes is sent to a few willing participants to ask if it resonated with their recollection of the discussion. The feedback from these participants affirms the accuracy of the interpretations.

4.4 Ethical Considerations

The Institutional Review Board of the authors’ university has obtained the study's ethical approval. Participation in the focus groups was voluntary and all participants offered informed consent after being informed about the study’s purpose and procedures. Confidentiality is highlighted due to the potentially delicate nature of discussing workplace stress and surveillance. Participants are assured that their identities will not be disclosed in any reports and that combined insights (not individual comments) will be shared with organizational leaders if requested.

It was emphasized that the participants should not share names or sensitive personal information. This was considered essential to creating a respectful atmosphere during the discussions. To ensure privacy, any possibly identifying details mentioned (such as specific project names or personal anecdotes) are generalized or omitted in the transcripts.

The moderator aimed to balance the conversation and encourage honest employee input. Therefore, no single group (e.g., managers) dominated, making it clear there were *no right or wrong answers*. Lastly, to mitigate any fear, the hypothetical nature of the AI system is

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

addressed. Participants were informed that it is an exploratory academic exercise and the discussion will not affect any current workplace monitoring. This reassurance was considered essential for maintaining ethical integrity. This would ensure that participants feel critical or express concerns about the AI concept without fear of consequences.

5. Results and Discussion

The focus group discussions yielded rich insights into how AI might be leveraged for proactive talent retention and the reservations and prerequisites associated with its use. Numerous key themes are presented below and supporting quotes from participants are revealed in the thematic analysis. Discussing these outcomes with interpretation and linkages to existing literature (i.e., a combined Results and Discussion section) is integrated for clarity. The major themes identified are: (1) Perceived Benefits of AI in Early Detection and Support, (2) Privacy and Surveillance Concerns, (3) The Necessity of Trust and Transparency, (4) The Role of Human Touch and Oversight and (5) Implementation Challenges and Recommendations. An overview of these themes and illustrative participant comments is provided in Table 1.

(1) Perceived Benefits of AI in Early Detection and Support: The potential *usefulness* of an AI-driven system to catch problems early is the dominant theme across all focus groups. Many participants, especially the HR managers, see value in the AI's potential to aggregate data and spot patterns that humans might miss. For instance, one HR manager noted, *"There are often red flags before someone quits – subtle changes like disengaging in meetings or slower response times. We [HR] can't monitor all that manually, so an AI that alerts us would be extremely helpful."* Employees, too, acknowledged benefits: *"If the system could tell I'm burning out before I even realize it, that could actually be good – it might suggest I take a breather or signal my manager to check on me,"* said a software developer. This sentiment reflects the suggestion of Basnet (2024) and Liang (2024) that AI can act as an early warning system, enabling preventive interventions rather than reactive measures. Participants imagine numerous supportive uses for the AI insights. Some mention the possibility of receiving personalized guidance – akin to a "virtual coach" – where the AI might recommend taking a day off after intensive work, or suggest speaking to a mentor. Others appreciate that the tool could help managers become more aware of team morale: *"Sometimes managers are the last to know when someone is unhappy. This could give them a heads-up to do something, like redistribute workload or just have a conversation,"* one team lead remarked. These perspectives align with the job resources side of the JD-R model. When the AI system functions to offer timely information and resources (such as breaks, support and adjustments), it is seen as a means to *reduce* job demands on employees and augment their well-being.

A few participants emphasize how AI may help overcome the stigma often associated with burnout or mental health issues. An employee points out, *"People don't always admit when they're burnt out or struggling. If the AI flags it based on data, it forces a conversation that may not happen otherwise."* Therefore, the AI is seen as a *neutral observer* that can assess genuine issues. It will also make it easier for employees to accept help (since data, not individual complaints, activate the intervention) by prompting managers to check in. This

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

finding echoes the idea that data-driven approaches can sometimes align with employee concerns that otherwise would have remained unknown. However, if employees trust the system's intentions, such benefits can only be realized, causing the following themes around trust and privacy.

(2) Privacy and Surveillance Concerns: The most frequently raised concern is about privacy – participants are wary of how much and what kind of data the AI system collects. A palpable discomfort is found at the thought of being closely monitored by an algorithm. As one participant said, *"Nobody wants Big Brother in the workplace. I don't want every Slack message and break I take to be watched."* This "surveillance" fear is echoed by others, who joked nervously about the AI reading their emails or timing their coffee breaks. Few HR managers, who stand to gain beneficial data from the system, acknowledged that *"If we go too far, employees will feel spied on and rebel – it can erode trust."* The data types that draw the most concerns are those perceived as personal, including communications (emails and chats) and any off-work hours data (like after-hours login activity or health metrics from wearables). Participants are more comfortable with the AI utilizing objective work metrics (e.g., missed deadlines, work output and overtime hours logged) than combing through the text of communications or biometric data. As per this delineation, employees have an internal line between legitimate performance data and invasive personal data. It aligns with ethical recommendations in the literature that advise utilizing the least intrusive data necessary for predictive models.

Some employees fear an AI system can be a "backdoor to micromanagement." One experienced engineer shared a scenario: *"I'm worried they'll start using this for productivity scoring – like if I'm not active for 10 minutes, it flags me. They say it's about burnout, but what if it's also used to measure our every move?"*. This comment discloses a trust deficit; employees may suspect that under the pretext of wellness, the company can present monitoring that is later utilized punitively or to push productivity, a concern consistent with findings in other studies on AI monitoring anxieties, Majumder and Misra, 2025.

The participants strongly felt that clear boundaries and policies are necessary to mitigate their concerns. It was also crucial that the company explicitly state how and what data will be collected and for what purposes it will be used. One of their biggest concerns was using data for promotions or punishment. Participating HR managers also agreed that a transparent data policy was essential and employees may be given the choice to opt out of specific data streams. This will improve their acceptability. Table 1 summarizes the widespread privacy theme, with 80% of participants explicitly mentioning concerns about being overly monitored (as shown by the frequency count in the focus group coding). To avoid being counterproductive, any AI retention system must be designed and communicated in a way that respects employee privacy.

(3) Necessity of Trust and Transparency: Trust emerges as a pivotal factor determining the success or failure of AI-driven retention efforts. In this context, it has multiple dimensions – trust in the *accuracy* and *fairness* of the AI and trust in management's intentions for using the AI. On the first aspect, participants are curious (and skeptical) about how accurately an

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algorithm can assess something as human as burnout or the intention to quit. *"People are complicated – can an AI really understand if I'm just having a bad week versus actually burning out?"* a participant asked. Employees are concerned about false positives (the AI wrongly flagging someone as at-risk) and false negatives (missing someone quietly struggling). A false favorable scenario is seen as potentially embarrassing or harmful: *"Imagine your manager calls you in because the AI said you're burnt out, but you're actually fine – that will be awkward and maybe make you doubt yourself,"* one person noted. Conversely, missing a genuinely at-risk employee means the system fails at its very purpose. These concerns indicate that employees will need evidence of the AI's validity. HR participants mention piloting the system and checking its predictions against real cases (e.g., comparing AI risk scores with actual turnover or burnout survey results) to ensure it works as intended. Human-AI Collaboration is the most appropriate approach, as emphasized in the literature. Building transparency about the functioning of AI is **crucial.** Participants were keen to know comprehensively what factors the AI looks at and relatively weighs in evaluation.

This feedback mirrors Meenu Chaudhary et al. (in 2025), who recommend utilizing explainable models and sharing feature importance with end-users. One HR manager said, *"We'd have to educate our workforce: like, 'the AI monitors these five things and if three of them change significantly, it triggers an alert, here's why.' Otherwise, rumors will fill the gap."* Indeed, insufficient information can result in worst-case assumptions, while transparency can reassure employees that the system is fair and does not make arbitrary judgments. Some employees also express that seeing some output of the AI for themselves can help – for instance, an employee may have access to their own "wellness dashboard" representing how they're doing on the AI's metrics. This suggestion aligns with a participatory approach: if employees can observe and verify the data being gathered about them, then it offers them a sense of control and an opportunity to correct any inaccuracies (like if the system logs a period of inactivity that is a work offsite with no network access).

Trust in management's intentions is equally critical. Most participants will consider the AI tool only if they believe leadership genuinely cares about EWB, not just productivity or cost savings. In the words of one participant, *"If this is just used to squeeze more out of us, then no thanks. But, if it's truly to help us not burn out, then that needs to be proven by how they respond to the data."* Employees perceive how managers respond when the AI flags issues: do they render support and solutions, or do they note it and expect the employee to figure it out? An HR participant shared a positive instance: *"If the AI shows someone's workload is too high, we as managers should be ready to redistribute tasks or bring in extra help. That'll show we're using this to support, not to judge."* This comment highlights that introducing AI should accompany manager training and a supportive culture. Or else, mistrust will undermine the effectiveness of the technology, no matter how good it is. The literature on AI in HR echoes this, emphasizing that a human-centric approach (where AI augments human decision-making benevolently) is principal for acceptance.

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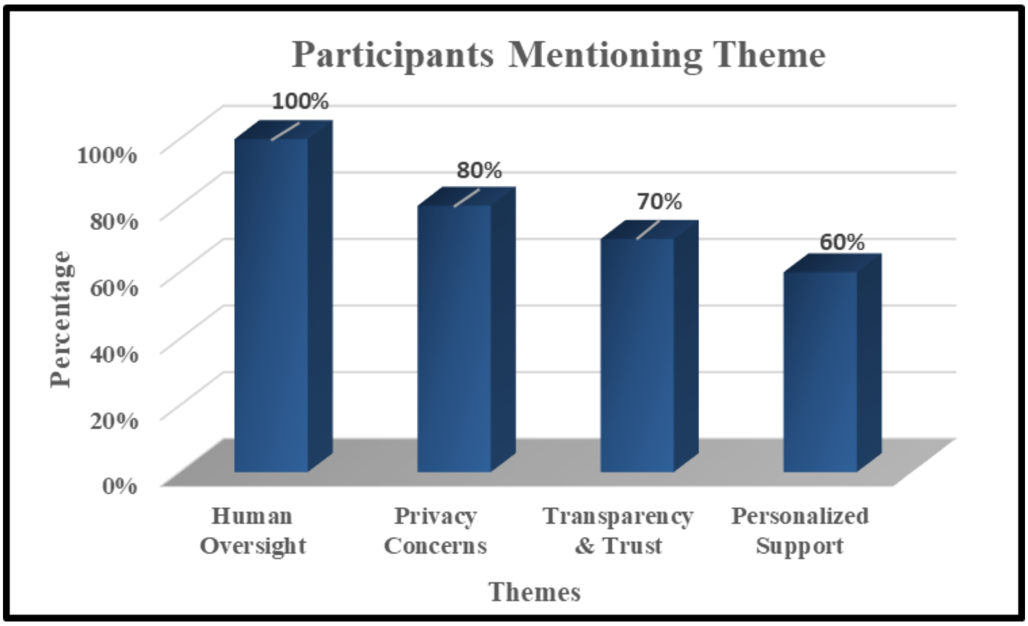

Figure 2: Focus Group Discussion – Key Themes

Source: Authors basis data of respondents

Figure 2 shows the percentage of participants (N = 10 per focus group, aggregated) who mention each major theme during the discussions, indicating the prominence of each concern or perception within the group. All participants (100%) mention "Human Oversight" (ensuring AI is partnered with manager judgment), underscoring a unanimous view on its importance. "Privacy Concerns" are raised by 80% of participants, "Transparency & Trust" issues by 70% and positive views on "Personalized Support" from AI by 60% of participants.

(4) Role of Human Touch and Oversight: Each focus group highlights that AI should not replace human judgment or empathy in EWB. When discussing how interventions should be implemented, participants repeatedly use phrases like "human touch," "empathy," and "understanding". There is consensus that if an AI alerts to a potential problem, it is still a human manager or HR professional's responsibility to approach the employee respectfully. *"The AI may tell you something's up, but it can't sit down and have a heart-to-heart talk. That's where a manager needs to step in,"* one participant remarked. Several employees emphasize that a supportive conversation, where the manager articulates care and renders assistance, is far better received than any automated notification or generic HR email. This aligns with optimal retention practices that underline the significance of the employee-supervisor relationship in addressing issues like burnout (a point supported by Basnet's note that supervisory support influences retention. Basnet (2024).

Human oversight is discussed regarding validation and context. AI may highlight data anomalies, but managers often have context that data alone cannot capture. For example, an HR participant described, *"If the AI flags Mark as high risk because he's been less active online, I (as his manager) know he's caring for a new baby at home this month – so, I interpret*

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that differently than if I had no context." In such cases, the manager doesn't jump to a burnout intervention; instead, they may offer Mark flexibility. Conversely, if AI misses something but a manager senses an issue (perhaps through tone of voice or other human cues), then the manager should trust their instinct and not be lulled into inaction by the absence of an AI alert. In the opinion of participants, Human-AI collaboration was the most appropriate approach. AI is very efficient in consistently providing data-based insight. Humans due to past experience offer understanding, intuition and personalized responses. This viewpoint corresponds with findings by researchers like Majumder and Misra (in 2025) who argue for AI systems that foster collaboration and trust between people and technology.

All participants agree that for the AI system to be accepted, it should be positioned clearly as a *support tool for managers* and an *empowerment tool for employees*, instead of an autonomous decision-maker. The phrase "augmented HR" came up, recommending that AI can augment HR professionals' abilities (by sifting through data and highlighting issues), but final decisions and interactions rest with humans. One focus group even suggests that the organization create a new role or designate a person as an "AI wellness champion" – someone in HR who monitors the AI outputs and coordinates follow-ups, ensuring a consistent and human-centric process to address any flags. This suggestion recommends a potential procedural innovation: instead of leaving each manager to figure out how to react, a trained specialist can handle first-line responses, speak with employees sensitively and then involve the manager as required. It exhibits participants' desire for *structured human oversight* to accompany the AI.

(5) Implementation Challenges and Recommendations: Beyond the issues of privacy and trust already covered, participants identify several challenges and concrete recommendations in discussing how to implement an AI-driven retention system successfully. One challenge is accuracy and avoiding bias – participants suggest a careful pilot phase, where the AI's predictions are tested and employees can receive feedback on whether the system's alerts are appropriate. One participant stated, *"Roll it out slowly, maybe in one department and learn from that. Don't just deploy company-wide without refining it."* This echoes the agile technique to technology implementation and is supported by the literature, which frequently calls for pilot studies when introducing AI in HR to calibrate systems to the company's culture and workforce specifics.

Ensuring employee buy-in is another challenge. Participants recommend involving employees in developing or selecting the AI tool, for instance, through surveys or a committee, to give them a voice. This participatory method can decrease fear of the unknown and make employees feel the tool is *for* them, not *against* them. A young professional in one group mentioned, *"Maybe some of us can volunteer to test it on ourselves and then share our experience. If our peers hear it isn't that scary and helped, they'll be more open to it."* Such peer testimonials can be a powerful way to build acceptance.

Training and communication plans are also emphasized. Managers need training on interpreting AI data and having conversations triggered by an AI alert. As noted above, the manner of intervention is significant – a recommendation is that managers receive specific

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guidance or even scripts on approaching an employee, concentrating on concern for the employee's well-being, instead of, for example, stating, "The data shows you're unproductive." Meanwhile, to preempt misconceptions, employees should be educated on what the system does and doesn't do, perhaps through town halls or FAQ documents.

Finally, participants discussed the significance of aligning the AI tool with organizational support systems. If the AI flags someone at high risk of burnout, the organization needs resources available to help, be it counsellors, the ability to redistribute workloads, or sufficient flexibility policies. An insightful comment is, *"The tool may tell you who needs help, but it's useless if there is no one to give help. Therefore, management must be prepared to take the necessary action, such as hiring temp support, adjusting deadlines and taking other measures.* This highlights that AI is just one available tool; effective retention also needs management dedication to take appropriate action based on the insights. Sometimes, investment in finding solutions may be required to mitigate burnout, such as hiring additional staff or changing practices.

Table 1 synthesizes the major themes from the focus groups, providing a summary and a verbatim example comment for each theme.

Table 1: Key Themes from Focus Groups on AI-Based Talent Retention

Theme	Summary of Participant Perspectives	Illustrative Quote from Participants
Usefulness of AI Alerts (Early Detection & Support)	Many see AI as helpful for catching burnout or attrition risks early, facilitating preventive support. AI can examine data and provide impartial alerts that prompt timely interventions (e.g., adjusting workload and offering help) before issues worsen.	"If the system can tell I'm burning out before I even realize it, that can be good – it may suggest I take a breather or signal my manager to check on me."
Privacy & Surveillance Concerns	Participants worry about extensive monitoring. They want clear limits on what data is collected and assurance that the system doesn't intrude on personal privacy or be misused for micromanagement. To alleviate this concern, transparency in data use and the option to opt out of certain tracking are recommended.	"Nobody wants Big Brother in the workplace. I don't need an AI reading my emails or timing my bathroom breaks – that's just going to freak people out."
Trust & Transparency (Accuracy and Fairness)	Trust in the system is crucial. Participants need to trust that the AI's predictions are accurate and fair. They ask for explainability (knowing how the AI reaches conclusions) and proof of concept (pilot results). It's crucial that the AI is presented as a tool to help employees, not to punish	"I'd want to know how the AI decides someone is at risk. If it's a black box, then I'm not going to just believe it. Show me the factors – like is it my overtime hours, my

	them and that management handles its insights with discretion and positive intent.	client ratings – so it makes sense.”
Need for Human Oversight & Empathy	Unanimous agreement that the human touch is irreplaceable. AI should augment managers, not replace them. Participants expect managers or HR to interpret AI alerts, communicate with employees with empathy and exercise judgment. A supportive conversation with a manager is considered the appropriate response to any AI flag. Human context (knowing personal situations) is essential to avoid misinterpretation of data.	“The AI may flag someone, but it can’t have a human conversation. Still need a manager to sit down and say, ‘Hey, I noticed you’ve been stressed, how can I help?’ The tool can’t show real empathy.”
Implementation & Training (Ensuring Effective Use)	The success of such a system relies on careful implementation. Suggestions comprise starting with a pilot program, providing thorough training for managers on using AI insights, communicating clearly to all staff about the purpose and limitations of the AI and integrating the tool with existing wellness resources. Participants also feel that employees should be involved in the rollout to gain buy-in. Organizational commitment to act on the AI’s findings (e.g., decreasing workloads and offering assistance) is critical for credibility.	“Don’t just drop this on us. Conduct a trial, show us the results and then tweak it. Train managers on how to approach us when the system flags an issue. If they just dump data on us without support, then it’s going to fail.”

6. Conclusion

This study examines the application of AI for proactive talent retention, focusing on how predictive analytics could anticipate employee burnout and impending turnover (job abandonment) to enable organizations to intervene early. Regarding the perceived advantages, concerns and implementation challenges of AI-driven retention strategies, insights from HR professionals and employees were gathered via a qualitative focus group approach. The findings painted a cautiously optimistic picture. On the one hand, the participants recognized the significant potential of AI tools to enhance retention. AI could identify early signs of burnout or disengagement that managers might overlook by analyzing extensive workplace data, enabling timely and personalized interventions. In contrast, critical human and ethical factors that determined the success of AI in this domain were highlighted in the research. The study’s focus group discussions reinforced the idea that AI should act as a decision-support tool, rather than a decision-maker. Nevertheless, careful navigation of privacy concerns and a steadfast commitment to keep the “human” in HRs were required to achieve these outcomes.

Practical implications: This study offered several actionable insights for HR practitioners and organizational leaders considering AI for ER. Initially, stakeholders involved the employees in

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communicating transparently about what the system would do. Additionally, real concerns were addressed through the co-design aspect.

Limitations: The research was conducted within a single firm and cultural context, which might affect the transferability of the findings. With varying privacy and data norms, participant views might differ in organizations with diverse cultures or industries (e.g., tech companies vs. public sector agencies).

Future research: In the future**,** practical lessons and personal narratives that deepen the understanding of the human-AI dynamics in workplaces will be yielded by the research focusing on those who have already experienced an AI-based retention or wellness program (as these become more common).

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