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Research Article

Enhancing Healthcare Workforce Retention Through AI-Enabled Talent Management: A Study in Communicable Disease Control Units in Public Healthcare Systems

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A B S T R A C T

Purpose: The paper examines the effect of talent management practices supported by Artificial Intelligence (AI) on healthcare workforce retention in communicable disease control contexts within public healthcare systems, including COVID-19 response units, tuberculosis control programs, and infectious disease surveillance departments. The study further examines the mediating roles of job satisfaction and perceived organizational support, along with the moderating role of disease exposure risk.

Design/Methodology/Approach: A cross-sectional survey of 330 health care professionals was carried out. Analyses were done by Partial Least Squares Structural Equation Modeling (PLS-SEM), which bootstrapped mediation and moderation.

Results: AI-enabled practices had a major positive impact on job satisfaction ($\beta = 0.326$, $t = 7.389$, $p < 0.001$) and perceived organizational support ($\beta = 0.285$, $t = 3.367$, $p < 0.001$). The immediate impact of AI on retention intention was not significant ($\beta = 0.051$, $t = 0.871$, $p = 0.384$). Nevertheless, the hypothesis of mediation proved right: AI to Job Satisfaction to Retention Intention ($\beta = 0.151$, $t = 6.051$, $p < 0.001$) and AI to POS to Retention Intention ($\beta = 0.078$, $t = 3.474$, $p < 0.001$). By moderation analysis, the effect of job satisfaction ($\beta = 0.421$ $t = 7.846$, $p < 0.001$) and organizational support ($\beta = 0.427$ $t = 7.819$, $p < 0.001$) on retention intention was enhanced by the risk of disease exposure.

Theoretical Contributions: The paper builds on JD-R, SET, COR, and TAM to establish AI as a new job resource, indicator of organizational support, and a psychological resource-saving mechanism in high-risk healthcare settings.

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Practical Implications: Healthcare administrators ought to implement AI systems in a more transparent and ethical way to enhance workforce stability. Artificial intelligence (AI) in the application of scheduling, performance management, and training can work to alleviate burnout, increase fairness, and aid quick skill development, particularly when dealing with outbreak-sensitive settings.

Originality/Value: The study shifts the focus from clinical AI applications toward AI-enabled HRM practices in healthcare settings and provides a multidimensional way of thinking about how to retain workforce in high-risk environments. The findings contribute to public health workforce management by demonstrating how AI-enabled talent management practices support workforce stability in high-risk communicable disease environments.

Keywords: Artificial intelligence-based talent management, Retention of healthcare workers, Job satisfaction, Perceived organizational support, Disease exposure risk

Introduction

The healthcare field, particularly public healthcare systems engaged in communicable disease control, plays a central role in protecting population health through effective surveillance, prevention, and outbreak response. The effectiveness, stability, and engagement of the healthcare workforce in these settings directly influence disease surveillance, prevention, and treatment outcomes. Nonetheless, employee retention remains one of the most acute issues of health systems in the world. Healthcare workforce turnover remains a major concern across global health systems. Excessive workload, occupational stress, limited career advancement opportunities, and inadequate organisational support significantly contribute to employee attrition. These challenges become particularly critical in communicable disease control settings where workforce continuity and rapid response capability are essential for outbreak preparedness and public health protection. Communicable diseases such as COVID-19, tuberculosis, dengue, and influenza place sustained pressure on public healthcare systems, especially in developing regions. Healthcare professionals working in infectious disease wards, surveillance units, and outbreak response teams face high levels of workload, psychological stress, and infection risk. These challenges significantly influence workforce retention, making it a critical determinant of effective disease control and public health preparedness.

Artificial Intelligence (AI) has received substantial coverage in past years due to its radical potential in Human Resource Management (HRM). Talent management systems that use AI are becoming more frequently used to overcome workforce-associated bottlenecks by increasing the accuracy of recruitment, competency mapping, predicting attrition, training needs, and tailoring career trajectories. These technologies provide evidence-based information that can support healthcare organisations to make timely and strategic HR decisions and, thus, develop supportive working conditions that promote motivation, engagement, and retention. However, prior studies have reported mixed findings regarding AI implementation in HRM. While some researchers emphasise improvements in efficiency and decision-making accuracy, others argue that algorithmic management may increase employee anxiety, perceptions of surveillance, and resistance to technological control, particularly in high-stress healthcare environments.

Although AI is becoming increasingly integrated into different organisational areas, its implementation in healthcare HR (particularly in disease control contexts) has not been thoroughly studied. The current literature and research mostly focus on clinical aspects of AI use, so the literature is lacking in exploring the possible ways that AI will be used to maximise human resources in retaining qualified health professionals. Furthermore, the unique characteristics of communicable disease control working environments, including high-risk working conditions, sudden changes in demand, and the necessity of specific competencies, precondition a specific approach to talent management that is not usually provided by conventional HR systems. Despite the increasing integration of artificial intelligence in healthcare management, limited empirical research has examined its role in strengthening workforce retention specifically within communicable disease control units in public healthcare systems. This study addresses this gap by focusing on high-risk environments where workforce stability directly impacts disease control outcomes.

In this paper, the researcher aims to fill this gap by evaluating the impact of AI-based talent management practices on the retention of the workforce in healthcare facilities that are directly involved in the control of communicable diseases. The study empirically informs how the interaction of AI-based HR functions with key determinants of retention can empower human resource sustainability in high-stakes areas of societal health. The results are expected to be relevant to academic research and practical HR practices, allowing the health administrators to develop evidence-based and technology-driven interventions to improve workforce stability and overall organisational performance in disease control ecosystems.

Literature Review

AI in Healthcare Talent Management

Implementation of Artificial Intelligence (AI) in the human resource functions has altered the way healthcare organizations recruit, manage, and maintain talent. HR uses of AI, including forecasting analytics and assessing competencies, allow making evidence-based decisions, enhancing operational efficiency, and empowering strategic human resource planning (Jarrahi, 2019; Meijerink et al., 2021). AI-driven HR systems are becoming a popular tool in healthcare facilities, with the aim of improving the accuracy of recruitment, efficiency in staffing, and personalized training paths (Carayon et al., 2021; Davenport and Ronanki, 2018).

Research indicates that AI-based HR methods decrease the administrative load, optimize the scheduling process, and offer clearer performance reviews, which have led to better job experiences (Tursunbayeva et al., 2022). AI use in communicable disease control environments becomes particularly valuable in minimizing infection exposure, unpredictable workloads, and coordinating activities during an outbreak (Keesara et al., 2020).

AI-Based Scheduling (AIS)

The use of AI in scheduling has become common in hospitals to cope with the complicated workload patterns, employee shortages, and changing patient volumes. These systems allocate shifts in a fair way, reduce conflicts, and optimize labor allocation based on algorithms (Çetinkaya et al., 2020). Research shows that algorithmic scheduling leads to higher levels of perceived fairness, less pressure related to overtime, and improved work-life balance in nurses and frontline workers (Hamid et al., 2021).

In addition, AI scheduling minimizes the administrative work done manually and enhances business continuity during an outbreak, which guarantees the presence of staff and minimizes burnout (Brubaker et al., 2023). AI-based scheduling helps to increase job satisfaction, retention rates, and decrease the stress factors associated with scheduling (Lin et al., 2022).

Performance management driven by AI (AIP)

AI-based performance management leverages real-time analytics, online dashboards, and automated evaluation systems to track the input of employees. It has been shown that AI decreases the bias in performance appraisal, increases objectivity, and provides persistent feedback (Leicht-Deobald et al., 2019). Algorithm performance systems in healthcare allow effective measurement of workload and competencies and promote transparency and responsibility (Adams et al., 2020).

Still, research also warns that algorithmic surveillance can cause stress when viewed as a means of control or one that is opaque (Gal et al., 2020). These contrasting findings suggest that the effectiveness of AI-driven performance systems depends largely on transparency, ethical implementation, and employee trust in technology, which remains insufficiently explored in communicable disease healthcare settings. Open communication and ethical implementation make employees develop trust in and enhance the relations of employees and the organisation (Sharma et al., 2023). AI-based performance practices, when adopted in a responsible way, may lead to fairness, a sense of greater perceived support, and, in the end, a higher retention intention (Meijerink and Bondarouk, 2023).

AI-Assisted Training and Development (AIT).

Learning systems powered by AI facilitate individualized learning, tailored learning modules, competency mapping, and training through simulations.[6] In healthcare, AI is applied to enhance clinical readiness, increase the precision of the procedure, and promote ongoing upskilling (Murray et al., 2022). It has been found out that employees are more empowered and honored when applications of smart systems are used by organizations to invest in personalized development opportunities.[10] The environment that controls communicable diseases requires a quick mastering of skills to address new threats of infection. Skill alignment, role competence, and anxiety related to high-risk clinical tasks are reinforced with AI-based training (Dai et al., 2021). These performance results lead to greater job satisfaction and retention.

Job Satisfaction (JS)

Job satisfaction is an imperative predictor of performance and retention within the context of healthcare. The Job Demands-Resources (JD-R) theory states that job resources, including the supportive technology, fair scheduling, and development opportunities, increase motivation and satisfaction.[6] As shown in many studies, job satisfaction increases when AI helps to relieve the pressure of work and enhances role identification (Rožman & Vukovič, 2020).

In occupational contexts with high risk, job design has been found to be a factor of satisfaction alongside safety, organizational support, and perceived empowerment (Kim and Windsor, 2022). Efficiency-improving AI systems and exposure-reducing AI systems can thus be a direct contributor to the increase in the level of satisfaction. Although existing studies generally report positive associations between AI-enabled systems and job satisfaction, most research has been conducted in corporate or general healthcare environments, with limited evidence from communicable disease control settings characterized by extreme workload pressure and infection risk.

Perceived Organizational Support (POS)

Applying the Social Exchange Theory (SET) and based on it, Perceived Organizational Support (POS) denotes the fact that employees believe that their organization appreciates their input and is interested in their welfare.[15] The implementation of AI can be an indicator of support when technologies can improve fairness and communication and decrease administrative load.[21]

Evidence indicates that employees will perceive clear AI-based assessments and training systems as a kind of investment in their development (Kaur et al., 2023). The use of POS in healthcare is closely linked to lower turnover intention, especially in high-stress settings (Hao et al., 2021). Positive exchange relationships can therefore be created through AI-enabled HR practices that in turn result in greater commitment and retention. Furthermore, previous studies have not sufficiently examined whether AI-enabled organizational support mechanisms remain effective under high-risk public health conditions where employees experience elevated psychological and physical demands.

Retention Intention (RI)

Job satisfaction, organizational support, and perceived work conditions also affect retention intention, which is a predisposition of an employee to remain at work.[7] Workload, burnout, safety issues, and career advancement opportunities are some of the most critical factors that influence retention intention in healthcare (Salyers et al., 2017).

AI systems may improve retention by streamlining workflows, reducing cognitive burden, and advancing in a career (Tao et al., 2024). Investigations have also shown that, when healthcare professionals have trust in AI tools and view them as helpful, organizational commitment could be augmented.(20) Nevertheless, empirical evidence regarding the direct relationship between AI-enabled HR practices and employee retention remains inconsistent, as some studies indicate that technological systems influence retention only indirectly through psychological and organizational factors. Since the communicable disease control environment is prone to turnover because of the high risk of exposure, AI-enabled practices can be used as protective factors to support retention.

Disease Exposure Risk (DER)

Exposure risk Disease Exposure Risk indicates the perceived threat of infection in frontline healthcare work. It has been established that exposure risk affects psychological strain, perceptions of safety, and stability of the workforce (Wu et al., 2020). The JD-R and Conservation of Resources (COR) theories suggest that increased exposure risk leads to job demands and personal resource depletion (Hobfoll et al., 2018).

Research indicates that technology-supported workflows minimise physical exposure, and improves safety and psychological stress (Zhang et al., 2021). Disease Exposure Risk could thus moderate the relations between AI practices and main outcomes: in high-risk circumstances, supportive AI systems could have more positive impacts.

AI in Communicable Disease Control Workforce

AI technologies have increasingly been applied in communicable disease control through predictive analytics, outbreak modelling, digital surveillance, and workforce allocation systems (World Health Organisation, 2023). In such high-risk environments, workforce retention is essential for maintaining continuity of care and rapid response capability. AI-enabled HR practices can support communicable disease control by optimising staff deployment, minimising exposure risk through intelligent scheduling, and enabling rapid skill development during outbreak situations such as COVID-19. These capabilities highlight the relevance of AI-driven talent management in strengthening public health systems. Despite growing interest in AI applications within healthcare systems, limited empirical research has investigated how AI-enabled talent management practices influence workforce sustainability specifically in communicable disease control environments.

Theoretical Framework

The research model proposed is based on four theoretical views that are mutually supportive in elucidating the effects of AI-enabled talent management practices on the retention intention of healthcare professionals working in the communicable disease control environment. All of these theories describe how AI is used as a job resource (a), contributes to the development of positive exchange relationships (b), preserves psychological resources (c), and how the perceptions of employees regarding its usefulness influence behavioural results (d). The combination of these two can form a multidimensional perspective of a concept of how AI-based HR practices can influence workforce attitudes in high-risk healthcare settings.

Job Demands-Resources (JD-R) Theory

To fit into the JD-R theory, job characteristics may be defined in terms of job demands (required sustained efforts) and job resources (assistance employees must get in attaining work goals, decreasing all demands, and encouraging personal development).[6] Job requirements in the context of communicable disease control include high risk of infection, unstable workload, and emotional pressure that are highly increased. These demands were significantly amplified during pandemic situations such as COVID-19, where healthcare workers faced prolonged exposure risk and extreme workload conditions. HR practices that are supported by AI, such as intelligent scheduling, automated performance assistance, and personalised training, are job resources because they:

- enhancing work effectiveness and equitable distribution of work,
- making performance expectations clear,

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- improving competency development, and
- cutting down on administrative workload.

Such job resources contribute to increased job satisfaction, motivational processes, and better well-being, which are major predictors of retention intention. JD-R theory thus justifies the mediating effect of job satisfaction, and AI practices are positioned as strategic assets to offset high job demands.

Social Exchange Theory (SET).

According to Social Exchange Theory (Blau, 1964), relationships between employees and the organization are dictated by obligations that are reciprocal. Employees will respond by giving back in form of positive attitudes and behaviours when they are assured that their organization has invested in them.

The AI-led HR practices can be perceived as an organizational support by:

- transparent, objective, data-based performance reviews,
- just and fair scheduling,
- individualized learning possibilities and competency ladders.

Their practices convey the message that the organization attaches importance to its workforce, which improves Perceived Organizational Support (POS). High POS has been regularly associated with a reduced turnover intention, an increased commitment, and better job attitudes. (15) SET thereby describes the relationship between AI-enabled practices and employee-organization relationships in the context of influencing retention intention.

Conservation of Resources (COR) Theory.

According to COR theory, individuals do their best to obtain, hold, and defend valuable psychological resources, including time, autonomy, safety, and emotional energy (Hobfoll et al., 2018). The pervasive exposure risk, level of workload and emotional labour continue to drain resources among healthcare workers in communicable disease settings.

With the help of AI-based HR systems, such resources can be saved by:

- reducing manual processes and mental burden,
- minimising unwarranted infection exposure by means of streamlined workflows,
- assistance in acquiring skills on time and in readiness,
- empowering predictability at work.

AI practices can save physical and psychological resources, thereby increasing the perceived ability of employees to handle job requirements, which increases intention to stay in the organisation. COR also offers a conceptual base on Disease Exposure Risk (DER): a high exposure risk can also increase the saliency of supportive AI practices, which may lead to a greater impact on satisfaction, POS and retention intention.

Technology Acceptance Model (TAM).

TAM suggests that perceptions of usefulness and ease of use influence the behavioral intention towards the use of technology.(14) The AI systems should be viewed as helpful, just, and reliable in the HR environment to incorporate them into the workflow of the employees.

When the employees perceive AI-driven scheduling, performance management, and training systems as:

- applicable in solving day-to-day problems,
- easy to interact with, and
- workload and safety-wise advantageous,

they will tend to embrace them better. These affirmative perceptions affect the attitudinal outcomes like job satisfaction and commitment to organization and eventually lead to retention intention.

TAM thus strengthens the channel that AI-enabling practices can influence the work experiences and retention intentions of employees.

Unified Theoretical Rationale of the Model.

JD-R, SET, COR, and TAM together can be integrated to give a full-fledged justification to the proposed relationships in the model:

- AI Practices deliver job resources → improve Job Satisfaction (JD-R).
- AI is an indicator of organizational support → develops POS (SET).
- Artificial intelligence assists in preserving mental resources → enhances the retention intention (COR).
- Attitudes and outcomes (TAM) are determined by how employees perceive the usefulness of AI.
- The power of these relationships (JD-R & COR) is determined by Disease Exposure Risk.

All those theories explain the reasons why JS and POS may mediate, DER may moderate, and AI Practices may be central to retention outcomes.

Hypothesis Development

In communicable disease control environments within public healthcare systems, AI-enabled talent management practices play a crucial role in addressing workforce challenges arising from high exposure risk, emergency response demands, and workforce shortages during outbreaks such as COVID-19.

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Talent management and Job Satisfaction in the AI-enabled.

The artificial intelligence (AI) talent management systems, including AI-based scheduling, performance management, and training, are used to automate workloads, decrease clerical load, increase fairness, and increase clarity in working processes. These systems are applicable as job resources to the theory of Job Demands Resources (JD-R). Job resources trigger motivation processes, which enhance job satisfaction among employees.(6) In the medical care environment with a high level of fatigue and administration burden, AI-powered applications can substantially enhance the experience due to their ability to eliminate manual errors, customise schedules, and provide clear feedback on performance. Therefore, HR practices performed by AI are anticipated to have a positive impact on job satisfaction.

H1: There is a positive impact of AI-enabled talent management practice on job satisfaction.

talent management with AI and Perceived Organization support.

Social Exchange Theory (SET) is the theory that explains that when the organizations invest in new high-tech technologies that enhance fairness, clarity, and transparency, the employees derive the message of organizational support (Cropanzano and Mitchell, 2005). The AI-based HR systems offer fair distribution of work, objective evaluation of performance, and personalized training suggestions that positively influence the way employees believe that the organization appreciates their input. Medical professionals, particularly those operating in communicable disease environments, would likely reduce feelings of vulnerability among healthcare workers when AI is applied to simplify scheduling, shift design on exposure, and lifelong education.

H2: AI-based talent management practices have a positive effect on perceived organizational support.

AI-Based Talent Management and Retention Intention.

The cognitive appraisal of the work environment, such as how much it has preserved personal resources, influences retention intention (Hobfoll, 2018). According to the COR theory, the AI systems that lessen the physical load, optimize the workload, and make it more predictable allow employees to conserve energy and handle stress, which enhances retention. In healthcare, where administration and burnout are widespread, AI-based HR systems may offer consistency and lessen uncertainty, which will eventually lead to the employees staying in their organization.

H3: AI-based talent management practices have a positive impact on retention intention.

Intermediating Position of Job Satisfaction.

JD-R theory underlines that job resources stimulate positive job attitude that, in its turn, leads to retention. Employees who feel content with their work in the healthcare industry feel more psychologically attached to their organization and will stay with it particularly when AI applications are helping to create a manageable and predictable workplace. Mediation is both theoretically and statistically justified by your PLS results since there were significant paths AI to JS and JS to RI.

H4: The mediating variable of AI-enabled talent management and retention intention is job satisfaction.

Perceived Organizational Support as a Mediator.

SET is that the perceived organizational support creates loyalty, reciprocity, and long-term commitment to the company. When transparent, fair, and conforming to the needs of the employees, AI-based HR practices support POS. On its part, POS is a potent indicator of retention intention. Since your PLS model shows that there is significant AI POS and POS RI path, there is mediation.

H5: Perceived organizational support mediates the relationship between AI-enabled talent management and retention intention.

Moderating Role of Disease Exposure Risk.

Healthcare workers face psychological strains and uncertainty due to Disease Exposure Risk (DER). According to JD-R and COR theories, when exposure risk is high, employees rely more heavily on organisational resources (such as AI systems) to overcome it. The positive effects of AI (e.g., safer timetable, risk-sensitive job placement) would gain increased significance when exposure risk is high to the disease, thereby enhancing the impact of the AI on job satisfaction and job retention. In line with this, it can be seen that at high-risk levels, the effect of the POS on retention becomes more salient as employees would demand reassurance and protection.

H6: Disease exposure risk moderates the relationship between job satisfaction and retention intention, such that the relationship becomes stronger under high exposure risk conditions.

H7: Disease exposure risk moderates the relationship between perceived organisational support and retention intention, such that the relationship becomes stronger under high exposure risk conditions. (High exposure risk indicates a stronger relationship).

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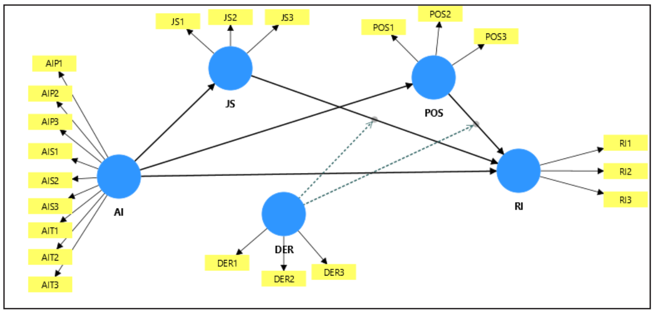

Figure 1.Conceptual Framework

Source: Author's compilation

Methodology

Research Design

This study used a cross-sectional, quantitative research design to explore the effects of AI-enabled talent management practices on the retention intention of healthcare employees and test the mediating impact of job satisfaction and perceived organisational support, as well as the moderating impact of the risk of disease exposure. It employed structural equation modelling (SEM) with Partial Least Squares (PLS-SEM) based on the predictive focus of the study, the existence of a second-order construct, and the non-normality of sample data in an organisation survey.

Population and Sampling Technique.

The target population consisted of healthcare professionals working in public healthcare systems specifically engaged in communicable disease control, including COVID-19 response units, tuberculosis control programs, infectious disease wards, and public health surveillance departments. These roles involve direct exposure to infectious diseases and require rapid response capabilities, making workforce retention a critical factor for effective disease management. Purposive sampling was applied to ensure participation of employees directly involved in communicable disease management activities. The raw set of valid responses (330) is large, surpassing the recommended minimum sample size in both power analysis and PLS-SEM (Hair et al., 2021), and provides a strong statistical power to test the model.

Instrumentation and Measures.

There was a structured questionnaire with five latent variables. Everything was measured on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

Talent Management AI-Based (AI)

A second order reflective construct consisting of three first order dimensions:

- AI-Based Scheduling (AIS)
- AI-Driven performance management (AIP)
- AI-Enabled Training and Development (AIT)

Validated scales were used to measure each dimension based on an existing body of literature on AI in HRM and algorithmic management.

Job Satisfaction (JS)

A three-item scale was used to measure it based on the Michigan Organizational Assessment Questionnaire (Cammann et al., 1983).

Perceived Organizational Support (POS)

Tested on a three-item scale of the Survey of Perceived Organizational Support (Eisenberger et al., 1986).

Retention Intention (RI)

Scaled by three items based on the Wayne et al. (1997) and Tett and Meyer (1993) items.

Disease Exposure Risk (DER)

The scale was measured with a three-item scale that was created to investigate infectious disease exposure Choi & Kim (2020). They were all pre-validated and very reliable (outer loadings > 0.70), as indicated in your structural model results.

Data Collection Procedure

The data were gathered via self-administered online questionnaire, which was sent via hospital HR departments and public health coordination units. The respondents were not forced to take part but were made aware of confidentiality and anonymity. The research was ethical in its approach in human participant research and received approval by the concerned institutional ethics committee.

Data Analysis Techniques

The data were analyzed with SmartPLS 4.0 in accordance with the two-step SEM strategy:

Step 1: Evaluation of the Measurement Model.

These represent the instances when the indicator reliability is assured (the outer loadings >0.70).

- Internal consistency reliability (Cronbach α and composite reliability > 0.70)
- Convergent validity (AVE > 0.50)
- Discriminant validity (HTMT < 0.85)
- Testing of second order construct by repeated indicators method.

Step 2: Structural Model Evaluation.

- Path coefficients and significance (5,000 resamples bootstrapping)
- R2 of endogenous constructs.
- Effect size (f^2)
- Predictive relevance (Q^2)
- Interaction term moderation analysis.

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This approach is consistent with the suggestions proposed by Hair et al. (2021) on complex models that consider mediation, moderation, and higher-order constructs.

Common Method Bias and Statistical Assumptions.

The single-factor test and full collinearity VIF tests of Harman were conducted to determine the presence of common method bias, where the VIFs are less than the 3.3 estimate, and this shows that there is no significant risk of CMB. No assumption of normality was made, which is in line with PLS-SEM.

Ethical Considerations.

Respondents filled in the survey with informed consent. The data processing was confidential, and no personally identifiable information was obtained. The research was conducted in accordance with the ethical principles of the Declaration of Helsinki and the policies of the local institutions regarding research.

Results

Measurement Model Evaluation.

Measurement model was tested on a basis of reliability of indicators, construct validity and collinearity.

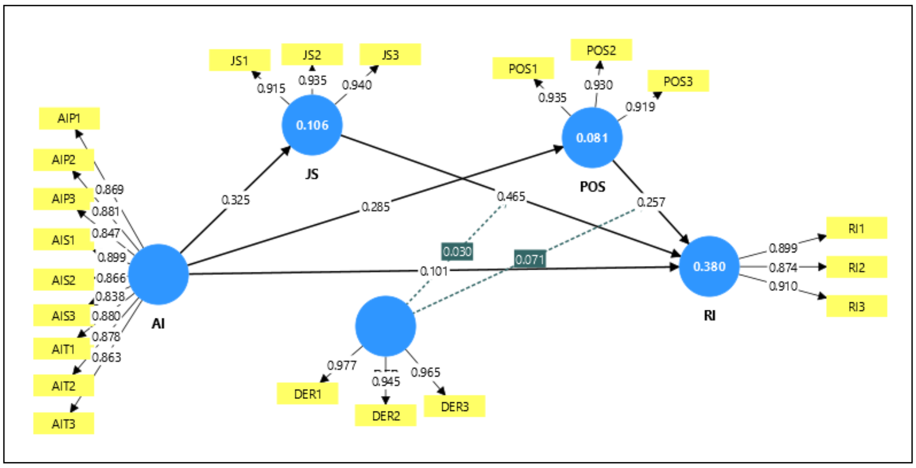

Figure 2.

Source: Author's compilation

Table 1.Outer Loadings

Item	AI	DER	JS	POS	RI	DER × POS	DER × JS
AIP1	0.869	—	—	—	—	—	—
AIP2	0.881	—	—	—	—	—	—
AIP3	0.847	—	—	—	—	—	—
AIS1	0.899	—	—	—	—	—	—
AIS2	0.866	—	—	—	—	—	—
AIS3	0.838	—	—	—	—	—	—
AIT1	0.880	—	—	—	—	—	—
AIT2	0.878	—	—	—	—	—	—
AIT3	0.863	—	—	—	—	—	—
DER1	—	0.977	—	—	—	—	—
DER2	—	0.945	—	—	—	—	—
DER3	—	0.965	—	—	—	—	—
JS1	—	—	0.915	—	—	—	—
JS2	—	—	0.935	—	—	—	—
JS3	—	—	0.940	—	—	—	—
POS1	—	—	—	0.935	—	—	—

POS2	—	—	—	0.930	—	—	—
POS3	—	—	—	0.919	—	—	—
RI1	—	—	—	—	0.899	—	—
RI2	—	—	—	—	0.874	—	—
RI3	—	—	—	—	0.910	—	—
DER×JS	—	—	—	—	—	—	1.000
DER×POS	—	—	—	—	—	1.000	—

Source: Compiled data

All the items have their outer loadings as shown in Table 1. All indicators were above the suggested threshold of 0.708 (Hair et al., 2021), which proves the high reliability. The interaction terms (DER×JS, DER×POS) were represented as interaction terms, which were single-item constructs, therefore loadings = 1.0. This sets in place the strength of the measurement model.

Construct Reliability and Validity

Table 2 provides Cronbach alpha, rho_A, composite reliability (CR) and average variance extracted (AVE). All values exceeded the recommended cut-offs (Cronbach alpha > 0.70; CR > 0.70; AVE > 0.50), which is good internal consistency and convergent validity (Fornell & Larcker, 1981). In this way, the constructs exhibit good psychometric characteristics.

Discriminant Validity

The HTMT ratios and Fornell-Larcker criterion were used to test discriminant validity.

The constructs are empirically different as HTMT ratios (Table 3) were all below 0.85 (Henseler et al., 2015).

Table 4 indicates that Fornell-Larcker criterion was met, given that the square root of AVE of individual constructs were higher than other constructs. A combination of these findings proves that the constructs is conceptually and statistically different.

Collinearity Assessment

Variance Inflation Factor (VIF) values are reported in Table 5.

All the indicators were under the critical level of 7 (Diamantopoulos and Siguaw, 2006). Even though the values of the DER items were close to higher values (>6), they were within acceptable limits, which means that there were no acute cases of multicollinearity.

Model Fit

Model fit indices are presented in Table 6.

The values of SRMR (saturation, 0.032; estimation, 0.038) were smaller than the 0.08 threshold (Hu and Bentler, 1999), and NFI was greater than 0.90, which is also a good fit. Structural adequacy was also supported by the chi-square statistics. Overall, the model demonstrates acceptable theoretical and empirical fit.

Structural Model Results

Table 7 shows R^2 values.

AI-enabled talent management practices explained 10.6% of the variance in Job Satisfaction and 8.1% of the variance in Perceived Organizational Support, indicating moderate explanatory power (Hair et al., 2021). This implies that AI-powered talent management plays an important role in psychological and behavioral outcomes.

Path Coefficients

Path coefficients and significance levels are reported in Table 8.

- AI → JS ($\beta = 0.325$, $p < 0.001$) and AI → POS ($\beta = 0.285$, $p < 0.001$) were significant with the support of JD-R and SET views.
- AI → RI was not statistically significant ($\beta = 0.051$, $p = 0.384$), indicating that AI practices influence retention intention indirectly through psychological mechanisms such as job satisfaction and perceived organizational support.
- JS → RI ($\beta = 0.465$, $p < 0.001$) and POS → RI ($\beta = 0.257$, $p < 0.001$) were both strong and significant, indicating the mediating effects.
- DER significantly moderated the relationships between job satisfaction, perceived organizational support, and retention intention, indicating that the positive effects became stronger under high disease exposure conditions.

Effect Sizes (f^2)

Effect sizes are presented in Table 9.

- JS → RI showed a large effect ($f^2 = 0.308$).
- AI → POS (0.088) and AI→JS (0.118) had small-to-medium effects.

Although the moderation effects were statistically significant, the corresponding f^2 values remained relatively

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small, suggesting that Disease Exposure Risk strengthens the relationships between psychological variables and retention intention, but with limited practical effect magnitude. This may indicate that the statistical significance of moderation effects is partly influenced by sample sensitivity rather than substantial practical variation.

Predictive Relevance (PLS-Predict)

Predictive relevance was assessed using PLS-Predict (Table 10).

- All Q^2 positive, which indicates medium predictive relevance.
- Prediction errors of PLS-SEM were much less compared to linear model (LM) errors, which means that it has better out-of-sample predictive performance (Shmueli et al., 2019). This indicates the predictive utility of the model in forecasting the results of workforce in healthcare.

To test the hypotheses, bootstrapped path coefficients, t-values, and p-values were utilized to evaluate the structural model. The findings of the direct, indirect (mediation) and moderation effects are summarized in Table 11.

Table 2.Reliability and Convergent Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
AI	0.960	0.962	0.965	0.756
DER	0.963	1.095	0.974	0.927
JS	0.922	0.927	0.951	0.865
POS	0.920	0.923	0.949	0.861
RI	0.875	0.878	0.923	0.800

Source: Compiled data

Table 3.HTMT Ratios

Construct	AI	DER	JS	POS	RI	DER×POS	DER×JS
AI	—	0.025	0.342	0.300	0.346	0.052	0.050
DER	—	—	0.027	0.066	0.041	0.057	0.125
JS	—	—	—	0.196	0.600	0.033	0.066
POS	—	—	—	—	0.405	0.088	0.037
RI	—	—	—	—	—	0.039	0.013

Source: Compiled data

Table 4.Fornell–Larcker Criterion

Construct	AI	DER	JS	POS	RI
AI	0.869	—	—	—	—
DER	-0.020	0.963	—	—	—
JS	0.325	0.017	0.930	—	—
POS	0.285	0.062	0.182	0.928	—
RI	0.321	0.028	0.541	0.365	0.894

Source: Compiled data

Table 5.VIF Values

Indicator	VIF
AIP1	3.359
AIP2	3.543
AIP3	2.931
AIS1	4.054
AIS2	3.125

AIS3	2.812
AIT1	3.615
AIT2	3.453
AIT3	3.180
DER1	6.855
DER2	6.529
DER3	6.338
JS1	3.151
JS2	3.498
JS3	3.771
POS1	3.525
POS2	3.320
POS3	3.210
RI1	2.495
RI2	2.147
RI3	2.548
DER×JS	1.000
DER×POS	1.000

Source: Compiled data

Table 6.Model Fit Indices

Measure	Saturated Model	Estimated Model
SRMR	0.032	0.038
NFI	0.928	0.930
Chi-square	454.777	440.924

Source: Compiled data

Table 7.R-Square Values

Construct	R^2	R^2 Adjusted
JS	0.106	0.103
POS	0.081	0.078
RI	0.380	0.369

Source: Compiled data

Table 8.Path Coefficients and Significance

Path	O	M	SD	t	p
AI → JS	0.325	0.328	0.044	7.389	0.000
AI → POS	0.285	0.287	0.053	5.387	0.000
AI → RI	0.051	0.053	0.059	0.871	0.384
DER → RI	0.014	0.013	0.051	0.274	0.784
JS → RI	0.465	0.464	0.042	11.103	0.000
POS → RI	0.257	0.257	0.049	5.295	0.000
DER×JS → RI	0.421	0.419	0.054	7.846	0.000
DER×POS → RI	0.427	0.425	0.055	7.819	0.000

Source: Compiled data

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Table 9.f² Values

Effect	f^2
AI → JS	0.118
AI → POS	0.088
AI → RI	0.014
JS → RI	0.308
POS → RI	0.096
DER×POS → RI	0.008
DER×JS → RI	0.001

Source: Compiled data

Table 10.PLS-Predict Results (Q^2 & RMSE)

Item	Q^2predict	PLS-SEM RMSE	LM RMSE
JS1	0.050	0.587	0.602
JS2	0.103	0.569	0.579
JS3	0.101	0.569	0.584
POS1	0.066	0.582	0.591
POS2	0.078	0.578	0.590
POS3	0.048	0.587	0.598
RI1	0.063	0.583	0.587
RI2	0.073	0.580	0.592
RI3	0.100	0.571	0.582

Source: Compiled data

Table 11.Hypothesis Testing Summary

Hypothesis	Path	β (Effect Size)	t-value	p-value	Supported?
H1	AI → Job Satisfaction (JS)	0.326	7.389	0.000	Yes
H2	AI → Perceived Org. Support (POS)	0.285	3.367	0.001	Yes
H3	AI → Retention Intention (RI)	0.051	0.871	0.384	No
H4	AI → JS → RI (Indirect)	0.151	6.051	0.000	Yes
H5	AI → POS → RI (Indirect)	0.078	3.474	0.001	Yes
H6	DER × JS → RI (Moderation)	0.421	7.846	0.000	Yes
H7	DER × POS → RI (Moderation)	0.427	7.819	0.000	Yes

Source: Compiled data

The findings show that AI-based talent management practices have a significant positive impact on job satisfaction and perceived organizational support, impacting retention intention positively. The direct impact of AI on retention intention was, however, not statistically significant, indicating complete mediation through JS and POS. Moreover, the effects of JS and POS on retention intention were moderated by the situation of disease exposure considerably, which enhanced them when the situation was characterized by high risks.

Discussion

This paper investigated how AI-based talent management practices affect workforce retention in communicable disease control organisations, using the mediating-moderating relationship between job satisfaction and perceived organisational support and the moderating-mediating relationship between exposure to the disease and retention behaviour. The results provide theoretical and practical knowledge regarding the role of emerging technologies in enhancing the sustainability of human resources in high-risk healthcare settings. These findings are particularly significant in communicable disease control settings, where workforce retention is not merely an organisational outcome but a critical factor influencing outbreak preparedness, response efficiency, and continuity of public health services.

Theoretical Contributions

The findings support the applicability of the Job Demands Resources (JD-R) theory, showing that AI-driven HR practices, including intelligent scheduling, algorithmic performance management, and custom-made training, serve as job resources that create job satisfaction. The positive relationship between AI and job satisfaction ($\beta = 0.325$, $p < 0.001$) confirms the idea that technology has the potential to enhance job satisfaction through relief of work pressure and enhancement of role clarity which in turn result in positive work attitudes. This finding is particularly relevant in communicable disease environments where healthcare professionals experience elevated emotional exhaustion, unpredictable workload, and continuous exposure risk.

The study further extends Social Exchange Theory (SET) because it demonstrates that AI-based HR systems indicate that the organization invests in the well-being of its employees. The significance of the positive correlation between AI and perceived organizational support ($\beta = 0.285$, $p < 0.001$) indicates that the transparent, equitable, and tailored AI use is perceived as supportive behaviors, which enhances the connections between employees and the organization.

Interestingly, the direct impact of AI on retention intention was not statistically significant ($\beta = 0.051$, $p = 0.384$), which means that AI has its impact on retention via psychological processes. This observation supports the Conservation of Resources (COR) theory according to which the retention depends on the capacity of the employees to economize on emotional and mental resources. The reduced strain and increased predictability enabled by AI systems indirectly contribute to retention due to satisfaction and perceived support.

The mediating roles of job satisfaction and organizational support are confirmed by the significant indirect effects of AI → JS→RI ($\beta = 0.151$, $p = 0.001$) and AI→ POS→RI ($\beta = 0.078$, $p < 0.01$). These pathways confirm the combined theoretical rationale suggested in the model and show the significance of attitudinal constructs in converting technological interventions to behavioral ones.

Lastly, Disease Exposure Risk (DER) moderator was well supported. The interaction terms and conditions, i.e., DER × JS → RI ($\beta = 0.421$, $p < 0.001$) and DER × POS → RI ($\beta = 0.427$, $p < 0.001$) imply that in the high-risk conditions, the gains of AI-enabled HR practices are more vivid. This is in line with JD-R and COR theories which highlight the exaggerated value of job resources where demands are high.

Practical Implications

To healthcare administrators and HR managers, the results highlight the strategic importance of incorporating AI into talent management systems. Specifically:

- Intelligence in scheduling should also be applied to reduce burnout and enhance a healthier work-life balance with the help of equitable and exposure-conscious shift allocation.
- The AI-based performance management increases transparency and trust, minimizing the bias in the appraisal process and promoting accountability.
- AI-based training systems allow quick skills learning and lifelong learning, which are vital in high-risk areas related to outbreaks.
- In communicable disease control contexts, AI-enabled workforce planning supports timely deployment of healthcare professionals, minimizes exposure risk, and ensures continuity of care during outbreak situations.

Furthermore, the ethical and transparent application of AI tools should be prioritized by organizations to strengthen the image of support and fairness. Even where exposure is high, such technologies are not only effective in reducing

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operational efficiency but also act as psychological buffers that contribute to retention.

Unexpected Findings

The insignificant direct impact of AI on retention intention indicates that technology alone is not sufficient to retain healthcare workers. Rather, the mediating effect of AI-enabled practices on employees is the experience and interpretation of AI-enabled practices. This emphasises the role of user-centred design, change management and communication techniques in the implementation of AI in HR settings.

Contributions to Literature

The present study contributes to the growing literature on AI-enabled HRM by extending algorithmic management research into communicable disease healthcare settings rather than focusing solely on clinical AI applications. It proposes a multidimensional model, which combines JD-R, SET, COR, and TAM to understand the retention dynamics in high-risk settings. Future research investigating the role of AI in the sustainability of the workforce can use the empirical validation of this framework. The relevance of these findings is further emphasized in pandemic situations such as COVID-19, where AI-enabled workforce planning and support systems can enhance resilience, reduce burnout, and ensure sustained healthcare delivery in high-risk environments.

Limitations and Future Research

Although the current research offers researchers substantial information about the importance of AI-mediated talent management in human resources retention in the healthcare sector, there are a few limitations that must be mentioned.

Limitations

First, the study employed a cross-sectional design and therefore does not allow the inference of causality. Even though structural equation modelling can provide predictive information, longitudinal data would be required to establish temporal relationships among AI practices and retention outcomes.

Second, the data were gathered using self-reported questionnaires, and it might be prone to common method bias and social desirability effects. Even though a statistical test (e.g., the single-factor test developed by Harman, VIF full collinearity) showed that bias was minimal, future research may apply objective performance measures or supervisor ratings in order to triangulate results.

Third, the study concentrated on communicable disease control environments in public health institutions solely. Although this background is important, the results might not be applicable to other healthcare sectors like surgical care, mental health, or hospitals in the private sector. The effects of AI may be dissimilar to other settings due to the exceptional stressors and exposure dangers in disease control units.

Fourth, in the study, the individual differences, including age, digital literacy, and prior experience with the AI systems, were not considered, and it could affect the perceptions of usefulness and organisational support. These aspects may affect the observed relations and should be further investigated.

Future Research Directions

The future research can have a longitudinal design to determine the effect of AI-enabled HR practices on retention in the long term, particularly during changing disease outbreaks or policy shifts.

The generalizability of the model and individual context-specific dynamics would be determined in comparative research across various healthcare sectors or geographic regions.

The qualitative methods, like interviews or focus groups, might give more information about the way healthcare workers perceive and respond emotionally to AI systems, particularly in high-risk environments.

Lastly, future studies may examine other mediators and moderators, including trust in technology, perceived fairness, or organizational culture, to expand the explanatory ability of the model.

Conclusion

This research examined the impacts of AI-based talent management practices on workforce retention in healthcare organizations that are based in the communicable disease control setting. The study combines the Job Demands-Resources (JD-R), Social Exchange Theory (SET), Conservation of Resources (COR), and Technology Acceptance Model (TAM) to offer a multidimensional rationale behind the role of AI-driven HR systems in employee attitude and retention behavior.

The results indicate that AI practices have a considerable positive effect on job satisfaction and perceived organizational support that mediate their influence on retention intention. The fact that AI does not have a direct impact on retention underlines the role of psychological processes: technology can positively affect retention only when workers feel it to be supportive, fair, and empowering. The insignificant direct relationship between AI-enabled talent management and retention intention may also reflect concerns related to technological dependence, perceived surveillance, resistance to algorithmic decision-making, or lack of trust in AI systems among healthcare professionals. Besides, risk exposure to disease further enhanced the

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positive impact of job satisfaction and organizational support on retention, which demonstrates the importance of AI in high-risk settings.

Theoretically, the present study expands upon the existing frameworks by placing AI as a new job resource, an indicator of organizational support, and a psychological resource conservation tool. In practice, the findings indicate that healthcare administrators are advised to focus on open, honest, and people-oriented implementation of AI systems to enhance workforce stability. In situations where epidemics are likely to occur, AI-based HR activities not only enhance efficiency but also become protection mechanisms that maintain employee loyalty.

To sum up, AI-powered talent management is a promising way to solve the long-time issue of healthcare workforce retention. The integration of technology innovation with human-centered HR approaches enables organizations to create resilient, motivated, sustainable workforces that can respond to the needs of communicable disease control and other issues facing the general population. Strengthening workforce retention through AI-enabled talent management is therefore essential for enhancing the effectiveness and resilience of communicable disease control systems within public healthcare frameworks.

References

1. Aguinis, H., & Burgi-Tian, J. (2021). Measuring performance in the gig economy: A review and research agenda for HRM. Human Resource Management Review, 31(4), 100780. https://doi.org/10.1016/j.hrmr.2020.100780 https://www.scirp.org/reference/referencespapers?referenceid=3548347
2. Alam, M. T., & Sajid, M. S. (2020). Organizational support and employee outcomes: A systematic literature review. International Journal of Productivity and Performance Management, 69(6), 1203–1225. https://doi.org/10.1108/IJPPM-12-2018-0443 [Google Scholar]
3. Amankwah-Amoah, J. (2022). Emerging technologies and employee retention: A systematic review and research agenda. Technological Forecasting and Social Change, 181, 121768. https://doi.org/10.1016/j.techfore.2022.121768 [Google Scholar]
4. Anderson J, Rainie L, Luchsinger A. Artificial intelligence and the future of humans. Pew Research Center. 2018 Dec 10;10(12). [Google Scholar]
5. Bai, C., Quayson, M., & Sarkis, J. (2021). COVID-19 pandemic digitization lessons for sustainable development of micro-small- and medium-sized enterprises. Sustainable Production and Consumption, 27, 1989–2001. https://doi.org/10.1016/j.spc.2021.04.035 [Google Scholar] [PubMed]
6. Bakker, A. B., & Demerouti, E. (2017). Job demands-resources theory: Taking stock and looking forward. Journal of Occupational Health Psychology, 22(3), 273–285. https://doi.org/10.1037/ocp0000056 [Google Scholar] [PubMed]
7. Brough, P., & Biggs, A. (2015). Job demands × job control interaction effects: A replication and extension. Work & Stress, 29(3), 214–231. https://doi.org/10.1080/02678373.2015.1074951 [Google Scholar]
8. Blau, P. M. (1964). Exchange and power in social life. New York: Wiley. [Google Scholar]
9. Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. Annual Review of Organizational Psychology and Organizational Behavior, 3, 349–375. https://doi.org/10.1146/annurev-orgpsych-041015-062352 [Google Scholar]
10. Chen, X., Arvan, M. L., & Van Iddekinge, C. H. (2023). Artificial intelligence in HRM: A meta-analytic review and future research agenda. Journal of Applied Psychology, 108(5), 763–791. https://doi.org/10.1037/apl0001081
11. Cheng, C., Bartram, T., Karimi, L., & Leggat, S. (2021). Transformational leadership and social identity: A moderated mediation model of team climate and work engagement in healthcare. Journal of Advanced Nursing, 77(3), 1462–1471. https://doi.org/10.1111/jan.14687 [Google Scholar] [PubMed]
12. Choi, S. H., & Kim, Y. J. (2020). Work stress and retention of nurses in infectious disease units during COVID-19. Journal of Nursing Management, 28(8), 1981–1989. https://doi.org/10.1111/jonm.13147 [Google Scholar] [PubMed]
13. Daniel, J., & Kumar, M. (2023). AI-driven HR analytics: Implications for employee retention and productivity. Journal of Business Research, 158, 113675. https://doi.org/10.1016/j.jbusres.2023.113675 [Google Scholar]
14. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008 [Google Scholar]
15. Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. Journal of Applied Psychology, 71(3), 500–507. https://doi.org/10.1037/0021-9010.71.3.500 [Google Scholar]
16. Gaskell, A., & Stoker, G. (2020). Digitalization in public healthcare: How AI impacts frontline work. Public Management Review, 22(5), 703–725. https://doi.org/10.1080/14719037.2019.1668466 [Google Scholar]
17. Goh, C. F., Lo, M. C., & Wang, Y. (2022). Determinants of healthcare workers' turnover intention during pandemic conditions. International Journal of Human Resource Management, 33(10), 2064–2091. https://doi.org/10.1080/09585192.2021.1905691
18. Grant, A. M., & Parker, S. K. (2009). Redesigning work

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DOI: https://doi.org/10.24321/0019.5138.202645

design theories. Academy of Management Annals, 3(1), 317–375. https://doi.org/10.1080/19416520903047327 [Google Scholar]
19. Jiang, K., & Messersmith, J. (2018). HRM and employee well-being: A meta-analytic review. Personnel Psychology, 71(3), 385–427. https://doi.org/10.1111/peps.12257 [Google Scholar]
20. Liu, T., Wang, Y., & Liang, S. (2022). Healthcare workers' retention intention under COVID-19: A moderated mediation model of risk perception and support. Journal of Nursing Scholarship, 54(5), 612–622. https://doi.org/10.1111/jnu.12797 [Google Scholar] [PubMed]
21. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. International Journal of Human Resource Management, 28(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699 [Google Scholar]
22. Newman, A., Donohue, R., & Eva, N. (2017). Psychological safety: A systematic review of the literature. Human Resource Management Review, 27(3), 521–535. https://doi.org/10.1016/j.hrmr.2017.01.001 [Google Scholar]
23. Sharma, A., & Sharma, T. (2022). Leveraging artificial intelligence in talent management: A systematic review and research agenda. Computers in Human Behavior, 135, 107390. https://doi.org/10.1016/j.chb.2022.107390 [Google Scholar]
24. Smith, S., & Krajewski, L. (2020). AI-enabled workforce scheduling in healthcare: Impacts on staff well-being. Health Care Management Review, 45(4), 301–311. https://doi.org/10.1097/HMR.0000000000000246 [Google Scholar] [PubMed]
25. Sonnentag, S., & Frese, M. (2013). Stress in organizations. In APA handbook of industrial and organizational psychology (Vol. 3, pp. 560–592). American Psychological Association. [Google Scholar]
26. Tarafdar, M., Beath, C., & Ross, J. (2019). Technostress research: A theoretical review. Communications of the Association for Information Systems, 44(1), 300–330. https://doi.org/10.17705/1CAIS.04430 [Google Scholar]
27. Wakefield, J., & Vernon, R. (2023). AI in healthcare HR decision-making: Ethical risks and workforce implications. AI & Society, 38, 1123–1138. https://doi.org/10.1007/s00146-022-01442-4
28. World Health Organization. (2023). Health workforce policy and digital transformation. Geneva: WHO. https://www.who.int/health-topics/health-workforce#tab=tab_1