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Artificial Intelligence in Workforce Medical Check-Up Programs Across the Employment Lifecycle: A Comprehensive Review

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ABSTRACT

Background: The demographic shift toward aging workforces and the rising prevalence of sedentary occupational disorders demand a paradigm shift in how occupational health is monitored across the employment lifecycle. Artificial intelligence (AI) offers transformative potential for medical check-up (MCU) programs by enabling predictive risk stratification, continuous physiological monitoring, and personalized preventive interventions. Objective: This review synthesizes evidence on AI applications across three workforce stages: pre-employment screening, routine occupational health monitoring, and post-retirement health maintenance, with emphasis on implications for regenerative and precision medicine. Methods: A systematic literature review was conducted using PubMed, Scopus, and Web of Science. Studies published up to 2025 were screened according to predefined inclusion criteria, focusing on peer-reviewed research examining AI applications in occupational health assessment, monitoring, and preventive care across different stages of the workforce lifecycle. Results: The reviewed studies indicate that AI can enhance pre-employment health screening through improved risk prediction and functional assessment. In routine occupational health monitoring, AI integrated with wearable technologies supports continuous physiological surveillance and early detection of health risks. For post-retirement populations, AI-driven biological aging models facilitate personalized health management and preventive intervention planning. Federated learning approaches also show promise for maintaining data privacy while enabling large-scale health analytics. However, current evidence remains constrained by limited prospective validation and heterogeneous study designsConclusions: AI-enabled MCU programs represent a critical frontier for precision occupational health, offering opportunities to improve risk assessment, disease prevention, and long-term workforce well-being. Nevertheless, challenges related to regulatory compliance, algorithmic fairness, data privacy, and clinical validation must be addressed before widespread implementation can be achieved.

INTRODUCTION

The global workforce is undergoing unprecedented demographic transformation. By 2050, individuals aged 65 years and older will constitute 16% of the global population, up from 10% in 2022. Concurrently, sedentary occupational behaviors now characterizing over 80% of modern jobs have been independently associated with increased risks of cardiovascular disease, type 2 diabetes, metabolic syndrome, and all-cause mortality. These converging trends necessitate a fundamental reimagining of occupational health surveillance, moving from episodic, reactive medical check-ups (MCUs) toward continuous, predictive, and personalized health management across the full employment lifecycle.

Artificial intelligence (AI) particularly deep learning, reinforcement learning, and federated learning has emerged as a transformative force in medicine, demonstrating expert-level performance in image interpretation, risk prediction, and biomarker discovery. In the occupational health domain, AI offers the capacity to integrate multimodal data streams (physiological signals, biomechanical measurements, electronic health records, and environmental sensors) into coherent risk profiles that evolve with the worker. This capability holds particular promise for three critical transition points: pre-employment screening, where baseline risk stratification can inform job matching; routine occupational monitoring, where early anomaly detection enables timely intervention; and post-retirement health maintenance, where personalized prevention can mitigate the physiological decline associated with occupational cessation. However, despite the growing use of AI in clinical medicine and workplace health monitoring, the evidence on AI-enabled MCU programs remains fragmented. Existing studies tend to focus on isolated applications, such as disease prediction, wearable-based monitoring, or automated image interpretation, rather than examining how AI can be systematically integrated into workforce MCU programs across the entire employment lifecycle. In particular, limited attention has been given to how AI-driven MCU systems can connect pre-employment assessment, ongoing occupational surveillance, and post-retirement health management within a unified precision-health framework. This lack of lifecycle-oriented synthesis constitutes a specific research gap that must be addressed to support the development of clinically valid, ethically responsible, and operationally feasible AI-enabled occupational health programs.

Key concepts central to this review include digital biomarkers quantifiable physiological and behavioral data captured by connected digital devices that can be used for disease detection and health monitoring; precision health a proactive approach that uses individual-level data to predict, prevent, and manage disease before clinical manifestation; occupational longevity the extension of healthspan throughout working life and into retirement; post-power syndrome a phenomenon describing accelerated physical and cognitive decline following departure from positions of authority or structured occupational engagement; and sedentary-related disorders a cluster of metabolic, musculoskeletal, and cardiovascular conditions arising from prolonged occupational sitting.

To address this gap,This review examines the current evidence base for AI applications in workforce MCU programs across pre-employment, occupational, and post-retirement stages, evaluates the clinical validity of different AI architectures, and discusses the ethical, regulatory, and implementation challenges that must be addressed for translation into practice within the framework of regenerative and precision medicine.

RESEARCH METHODS

Search Strategy

A systematic literature search was conducted in PubMed, Scopus, and Web of Science for articles published between January 2015 and July 2025. The search was completed in July 2025 and was designed to ensure transparency, reproducibility, and comprehensive coverage of studies applying artificial intelligence to occupational and workforce health contexts.Search terms combined three conceptual domains: (1) artificial intelligence terms ("artificial intelligence," "machine learning," "deep learning," "neural network," "reinforcement learning," "federated learning"); (2) occupational health terms ("occupational health," "pre-employment screening," "medical check-up," "workforce health," "employee health," "occupational monitoring"); and (3) lifecycle stage terms ("post-retirement," "aging workforce," "occupational longevity," "sedentary behavior," "health maintenance"). Boolean operators were used to combine domains, and reference lists of included articles were hand-searched for additional citations.

Inclusion and Exclusion Criteria

Inclusion criteria were: (1) original research articles, systematic reviews, or meta-analyses; (2) publication in top-tier peer-reviewed journals including Nature Medicine, The Lancet Digital Health, JAMA, NEJM, BMJ, IEEE Transactions on Medical Imaging, npj Digital Medicine, Cell Reports Medicine, Nature Aging, and Lancet journals; (3) direct application of AI/ML methods to workforce health screening, monitoring, or post-retirement health; and (4) English language publication.

Exclusion criteria were: (1) conference abstracts, preprints, grey literature, or publications from MDPI, Hindawi, Frontiers, or similar publishers; (2) studies limited to general population health without occupational context; (3) opinion pieces without original data; and (4) articles focusing solely on non-health AI applications (e.g., scheduling, payroll).

Data Extraction and Synthesis

Two reviewers independently extracted data on study design, population, AI architecture, performance metrics, validation approach, and regulatory considerations. A standardized data extraction form was used to ensure consistency across studies. Extracted information included author, year, country, study objective, occupational setting, participant characteristics, AI/ML technique, input data type, outcome measure, validation method, key findings, limitations, and quality appraisal resultDue to heterogeneity in study designs and outcome measures, a narrative synthesis approach was adopted, organized by workforce lifecycle stage.

RESULTS AND DISCUSSION

AI in Pre-Employment Screening

Pre-employment medical assessments traditionally rely on questionnaires, basic physical examinations, and laboratory testing approaches that have demonstrated limited predictive value for future occupational health outcomes. AI offers the potential to enhance risk stratification through integration of multimodal baseline data.

Cardiovascular Risk Prediction: Deep learning models applied to electrocardiogram (ECG) data have demonstrated the ability to predict 10-year heart failure risk with superior performance compared to conventional risk calculators. A study validating an ECG-based AI model across multiple cohorts reported improved discrimination for both heart failure with preserved ejection fraction (HFpEF) and reduced ejection fraction (HFrEF), with area under the curve (AUC) values exceeding 0.85. This approach could be integrated into pre-employment screening to identify candidates who may benefit from modified duty assignments or enhanced cardiovascular monitoring. In contrast to occupational monitoring, where cardiovascular AI is used to trigger immediate work-rest decisions, ECG-based screening is better suited for baseline risk stratification, job matching, and longitudinal surveillance planning.

Movement Competency and Musculoskeletal Risk: Musculoskeletal disorders represent a leading cause of work disability. A proof-of-principle study demonstrated that an AI model combining principal component analysis with linear discriminant analysis could classify lifting tasks as "low" or "high" exposure to spinal loading with >85% accuracy using only motion data. This approach offers a mechanism for proactive identification of candidates at elevated risk for work-related musculoskeletal injury, moving beyond traditional static strength testing toward dynamic movement competency assessment.

Cognitive and Mental Health Screening: Deep learning models have been developed to automate scoring of open-ended psychological assessments used in employee selection, achieving concordance with human expert raters. Furthermore, AI analysis of speech patterns and facial expressions during video interviews has shown promise in screening for mental health conditions, though ethical concerns regarding algorithmic bias in hiring decisions remain substantial.

Emerging Substance Use Screening: A recent Nature Medicine study demonstrated the feasibility of using AI to screen for opioid use disorder from electronic health record data, achieving AUC values of 0.78–0.86 across diverse healthcare systems. Integration of such screening into pre-employment health assessments could facilitate early referral to treatment programs while raising important questions about privacy and discrimination.

AI in Routine Occupational Health Monitoring

Continuous monitoring of workers' physiological status during occupational activities represents the most mature application domain for AI in workforce health. Compared with pre-employment and post-retirement applications, routine occupational monitoring has the strongest operational immediacy because AI outputs can be translated directly into alerts, adaptive scheduling, ergonomic modification, and real-time safety decisions.

Wearable Sensor Integration and Anomaly Detection: Several studies have demonstrated the feasibility of using wristband-type wearable biosensors to capture physiological signals including electrodermal activity (EDA), photoplethysmography (PPG), and skin temperature for real-time assessment of worker state. A study of eight construction workers using supervised machine learning (Gaussian support vector machine, GSVM) achieved 81.2% validation accuracy in distinguishing between low and high levels of perceived risk during actual work activities. This approach leverages the sympathetic nervous system's automatic response to hazard perception, providing a continuous, objective alternative to post-hoc survey methods.

Cardiovascular Strain Forecasting: Physical overexertion is a major contributor to occupational injuries, particularly in construction, manufacturing, and mining. A field study involving bridge maintenance workers used deep learning architectures including Long Short-Term Memory (LSTM) networks, Bidirectional LSTM, and Gated Recurrent Units (GRU) to forecast one-minute-ahead heart rate based on time-lagged physiological metrics [14]. LSTM demonstrated the best overall performance (MAE = 5.4 bpm, MAPE = 5.77%). Such predictive capability enables proactive work-rest scheduling and alerts before heart rate exceeds individualized safety thresholds, potentially preventing cardiovascular events and fatigue-related accidents.

Stress and Mental Workload Detection: Beyond physical strain, AI models have been applied to detect psychological stress in occupational settings. The Fit4Work system, designed for older office workers, used machine learning models to recognize physical activities, estimate energy expenditure, and detect mental stress, providing personalized lifestyle recommendations. Multi-modal sensing combining EEG, ECG, and behavioral data has enabled computational models of heart-brain interactions during work performance, suitable for integration into mobile platforms for online cognitive load assessment.

Sedentary Behavior Recognition: Prolonged occupational sitting is an independent risk factor for cardiometabolic disease. AI-based analysis of combined electromyography and accelerometry data has achieved high sensitivity (83–98%) and AUC values (0.85–0.91) for detecting sedentary behavior and active sitting. These systems can provide real-time feedback to interrupt prolonged sitting periods, addressing a critical workplace health priority.

AI in Post-Retirement Health Maintenance

The transition from active employment to retirement represents both a risk window and an opportunity for health intervention. Retirement is associated with changes in physical activity patterns, dietary habits, social engagement, and cognitive stimulation all of which influence health trajectories.

Post-Power Syndrome and Metabolic Decline: The phenomenon of accelerated health decline following retirement from positions of authority or high-structured occupational engagement termed "post-power syndrome" has been documented in both professional athletes and executives. A study of retired soccer players found that those who gained >12 kg after retirement had substantially higher risk of developing metabolic syndrome, with increased fat mass index nearly doubling the odds (OR = 1.9). AI-based predictive models could identify retirees at highest risk for adverse metabolic transitions based on pre-retirement trajectories and early post-retirement changes.

Deep Aging Clocks for Biological Age Assessment: Perhaps the most transformative AI application for post-retirement health is the development of deep aging clocks (DACs) neural network models trained on large-scale longitudinal datasets to estimate biological age from routine blood biomarkers. These models generate estimates more predictive of mortality, frailty, and disease onset than chronological age alone. As Zhavoronkov et al. argue, DACs should become essential tools in the physician's toolkit, enabling AI-supported recommendations for geroprotective interventions tailored to individual aging trajectories. The integration of DACs into post-retirement MCU programs could identify accelerated agers before clinical disease manifests, enabling timely lifestyle and pharmacological interventions.

Personalized Physical Activity and Fall Prevention: The retirement transition represents a "window of opportunity" for lifestyle modification. n-of-1 studies using wearable accelerometry have revealed substantial inter-individual variability in physical activity changes during retirement, with some individuals increasing activity while others become more sedentary. AI can identify individual determinants of PA behavior sleep quality, mood, time availability and deliver personalized interventions to maintain mobility and prevent the downward spiral of reduced activity leading to sarcopenia, metabolic decline, and increased fall risk.

Continuous Glucose Monitoring and Metabolic Management: Inclusion of continuous glucose monitoring (CGM) as part of worksite health screening has demonstrated the ability to provide personalized glycemic profiles that identify pre-diabetic states missed by conventional fasting glucose or HbA1c measurements. For post-retirement populations, AI-integrated CGM systems can provide closed-loop management of glycemic control, with the added benefit of detecting early metabolic deterioration associated with reduced occupational physical activity.

Comparison of AI Architectures and Clinical Validation

Deep Learning: Convolutional neural networks (CNNs) and LSTM networks dominate the occupational health literature. CNNs excel at pattern recognition in structured data (images, spectrograms), while LSTMs capture temporal dependencies in physiological time series. The construction worker HR forecasting study demonstrated that LSTM outperformed CNN, GRU, and hybrid architectures for one-minute-ahead prediction. However, deep learning models require substantial labeled training data and are susceptible to performance degradation when deployed in settings different from training environments. This limitation is especially important in occupational health because workforces differ by task type, environmental exposure, shift pattern, age distribution, comorbidity profile, and sensor availability. Therefore, strong internal accuracy does not necessarily indicate readiness for deployment unless external validation, calibration testing, and subgroup performance analysis are conducted across diverse workplace settings.

Reinforcement Learning: While reinforcement learning has shown promise in clinical decision-making (e.g., insulin dosing, sepsis management), its application to occupational health remains nascent. Theoretical frameworks suggest potential for dynamic work-rest scheduling optimization and adaptive intervention delivery, but no field studies have been identified.

Federated Learning: Privacy-preserving machine learning through federated learning where models are trained across decentralized institutions without sharing raw data has been systematically reviewed in healthcare applications. This architecture is particularly relevant for occupational health, where worker data must remain within employer or healthcare provider systems. Federated learning enables collaborative model development across organizations without compromising data sovereignty, though challenges remain in handling non-identically distributed data across sites.

Clinical Validation Status: The majority of occupational health AI studies remain at the proof-of-concept or retrospective validation stage. Prospective validation in real-world occupational settings is limited, and randomized controlled trials are virtually absent. This contrasts with clinical AI applications in radiology and dermatology, where regulatory-approved systems have demonstrated measurable improvements in workflow efficiency and diagnostic accuracy in prospective studies. The gap between technical performance and clinical utility in occupational health AI represents a critical research priority.

Ethical, Regulatory, and Data Privacy Frameworks

Data Privacy Under GDPR and HIPAA: Health data collected through occupational MCU programs are subject to complex regulatory frameworks. Under the European Union's General Data Protection Regulation (GDPR), health data constitute a special category requiring explicit consent and purpose limitation. The US Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule governs protected health information held by covered entities, but does not extend to data collected by employers through wellness programs or wearable devices unless handled by healthcare providers. This regulatory gap creates substantial ambiguity for employer-sponsored AI health monitoring programs. The ambiguity becomes more consequential when health monitoring is linked to employment decisions, productivity assessment, insurance eligibility, or return-to-work clearance. In such cases, AI systems may shift from preventive health tools into mechanisms of workplace surveillance, creating risks of discrimination, stigmatization, and loss of worker trust.

Algorithmic Fairness and Bias: AI models trained on occupational health data risk perpetuating existing disparities. A landmark study demonstrated that a commercial risk prediction algorithm used to guide clinical decisions for 200 million patients exhibited racial bias, systematically underestimating the health needs of Black patients due to biased training labels (healthcare costs rather than actual disease burden). Occupational health AI must be rigorously evaluated for demographic fairness across age, gender, race, and socioeconomic status to avoid reinforcing workplace inequities.

Informed Consent and Worker Autonomy: The continuous nature of AI-enabled health monitoring raises fundamental questions about informed consent. Workers may feel coerced into participating in health surveillance programs due to employment concerns, and the opacity of many AI models limits meaningful understanding of how data will be used. Ethical frameworks emphasize the importance of transparent communication regarding data use, the right to opt out without penalty, and governance structures that include worker representation.

Indonesian Health Data Standards: In the Indonesian context, the 2022 Personal Data Protection Law (Undang-Undang Perlindungan Data Pribadi) establishes requirements for data processing consent, purpose limitation, and cross-border data transfer restrictions. Implementation for occupational health AI must align with Ministry of Health regulations and the Indonesian National Health Insurance (JKN) data governance framework. However, specific guidelines for AI in occupational health screening are not yet established, creating both challenges and opportunities for proactive regulatory design.

Implications for Regenerative and Precision Medicine

AI-enabled MCU programs align with the core principles of precision medicine tailoring prevention and treatment to individual characteristics while extending the concept into the occupational domain. Deep aging clocks offer a mechanism for quantifying biological aging trajectories, enabling identification of individuals who may benefit from regenerative interventions (e.g., senolytic therapies, mitochondrial enhancement) before age-related functional decline manifests. Continuous monitoring through wearable sensors creates the data infrastructure for precision health detecting deviations from individual baselines rather than population norms, and enabling early intervention before disease develops.

The concept of occupational longevity maximizing healthspan across the working lifespan and into retirement requires integration of occupational, biomedical, and behavioral data into personalized risk profiles. This vision aligns with the learning health system paradigm, where data collected through routine care continuously inform and improve preventive strategies. However, realizing this vision requires substantial investment in data infrastructure, regulatory clarity, and workforce education to ensure that AI tools augment rather than replace clinical judgment. Equally important, implementation must include safeguards against function creep, where data initially collected for health promotion are later used for productivity monitoring, disciplinary action, or exclusion from employment opportunities. The success of AI-enabled occupational precision medicine will therefore depend not only on model performance, but also on transparent governance, independent validation, ethical oversight, and sustained worker trust.

CONCLUSION

Artificial intelligence offers transformative potential for workforce medical check-up programs across the full employment lifecycle. In pre-employment screening, AI-driven risk stratification using ECG, movement analysis, and cognitive assessment can inform job matching and baseline health surveillance. During routine occupational monitoring, wearable sensor-integrated deep learning models enable continuous physiological tracking, anomaly detection, and predictive forecasting of cardiovascular strain, stress, and perceived risk. For post-retirement populations, deep aging clocks and personalized intervention algorithms can mitigate the metabolic and functional declines associated with occupational cessation.

However, the field remains at an early stage of validation. The gap between retrospective technical performance and prospective clinical utility is substantial, with few studies demonstrating measurable improvements in occupational health outcomes through AI deployment. Critical challenges include regulatory alignment across jurisdictions (GDPR, HIPAA, Indonesian standards), algorithmic fairness to prevent exacerbation of health disparities, data privacy in employer-sponsored programs, and the need for prospective randomized trials demonstrating real-world impact.

For the emerging field of regenerative and precision medicine, AI-enabled occupational health programs represent both a proving ground and a deployment opportunity. The ability to quantify biological aging trajectories, detect presymptomatic deviations from individual baselines, and deliver personalized interventions across decades of workforce participation exemplifies the promise of precision health. Realizing this potential will require sustained collaboration among occupational health physicians, data scientists, ethicists, regulators, and most importantly the workers whose health these systems are designed to protect. To translate this potential into practice, occupational health providers should prioritize the phased implementation of validated AI tools for cardiovascular risk assessment, fatigue monitoring, and early disease detection within existing medical check-up programs. Policymakers should establish standardized governance frameworks that mandate algorithm transparency, periodic bias audits, informed worker consent, and secure health data management. In addition, future research should focus on multicenter prospective trials evaluating not only predictive accuracy but also tangible outcomes such as reduced occupational illness, improved work fitness decisions, lower healthcare costs, and enhanced worker well-being. These measures will help ensure that AI adoption in occupational health is evidence-based, equitable, and aligned with long-term workforce health objectives.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest related to this review. No financial, institutional, commercial, or personal relationships influenced the literature selection, analysis, interpretation, or writing of this article. The discussion of artificial intelligence applications in workforce medical check-up programs, occupational health monitoring, and post-retirement health maintenance was conducted independently and objectively.

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