DOI: 10.2478/rjom-2025-0001

Reviews

How can artificial intelligence be used within occupational medicine to identify early worker needs and improve workplace accommodation? A narrative review

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Abstract

Background: Artificial intelligence (AI) is now present in many areas of healthcare, but its role in occupational medicine is still unclear. The available literature comes from different fields that are only partly connected and is rarely viewed from an occupational-health perspective. This makes it hard to judge how such technologies could support prevention, follow-up, or workplace adjustments.

Aim: This paper explores how AI has been used or proposed to help identify early changes in workers' health needs and to guide the planning of workplace accommodations for those with chronic illnesses, with particular attention to evidence most relevant to occupational medicine.

Methods: A narrative review was conducted using predefined questions and eligibility criteria, and the material was organised thematically. Searches in major databases and several professional sources identified studies on AI in workplace health, monitoring of chronic conditions, return-to-work models, and accommodation planning. The selected publications were analysed along four themes: early identification of needs, workplace accommodation, potential contributions to occupational medicine, and the methodological and ethical limits that influence current developments.

Results: The studies describe various AI tools, including real-time monitoring systems, predictive models, wearables, decision-support applications, and digital platforms for self-management. These have been used to detect changes in functional capacity and to support more tailored workplace adjustments. Reported benefits include improved surveillance, more consistent diagnostic support, and some organisational advantages. However, evidence remains limited. Few tools have been tested in routine workplace conditions, and concerns about data quality, bias, privacy, confidentiality, and opaque algorithms persist.

Conclusions: AI is being explored as a complementary support for early needs detection and workplace accommodation, but current evidence is insufficient to draw firm conclusions about practical impact. Progress requires stronger validation, clearer algorithms, reliable ethical safeguards, and continued interdisciplinary collaboration.

Keywords*: artificial intelligence, occupational medicine, workplace accommodation, chronic illness, early needs detection, digital health.*

Introduction

Artificial intelligence (AI) has begun to shape everyday practice in several health-related fields. In many systems, it is used to sort information more efficiently and to flag issues that clinicians might want to examine in greater detail [1]. In occupational medicine, AI has attracted attention for its capacity to flag early changes in worker health requirements and to guide accommodation planning [2]. This matters particularly for chronic illnesses, where functional ability is variable and declines may precede clinical recognition [3]. Chronic illnesses such as diabetes, cardiovascular disease, respiratory disorders, and autoimmune conditions often interfere with a person's capacity to work and with overall productivity [4, 5]. Recognising early signs that additional support may be needed is important for sustaining safe and stable employment.

Traditional occupational medicine approaches rely on scheduled assessments or self-reported symptoms, which may miss subtle or early signs of functional decline [6]. Several AI applications, ranging from predictive models to sensor-based monitoring and digital decision aids, can generate a steady flow of information that may help refine preventive approaches and adjust support more quickly when problems appear [7]. Even so, the field is still fragmented: most tools differ widely in design and purpose, and only a few have been deployed under real working conditions [8]. Concerns about data reliability, bias in algorithms, and the handling of sensitive worker information continue to limit broader adoption, along with issues of transparency and fairness in how such systems are implemented [9, 10].

These gaps underline the value of a careful review of current research, one that can show more clearly how AI might assist with identifying worker needs at an earlier stage and with shaping accommodations that are genuinely useful in practice. This Structured Narrative Review examines how AI technologies are currently applied or proposed within occupational settings, evaluates potential benefits and risks, and identifies key evidence gaps. This review examines how different AI approaches are used to recognise changes in workers' health needs at an early stage and how they may inform the adaptation of work conditions for people living with chronic illness. It also considers the broader implications for occupational medicine and discusses the methodological and ethical issues that continue to shape this field. The discussion provides a basis for clinicians, employers, policymakers, and research teams who need a clearer view of how AI may contribute to safer and more flexible work environments.

Methods

This work follows the Structured Narrative Review approach, which is appropriate for fields where the evidence is varied and the concepts are still developing, as is the case with AI in occupational medicine. The review was guided by predefined questions and selection criteria, and the search and extraction steps were documented in detail to support methodological transparency.

Research Framework

One primary question and several secondary questions shaped the review. These guided the thematic analysis and kept the focus on how artificial intelligence (AI) may assist in identifying worker necessary workplace accommodations for people living with chronic illness in the earliest stage possible of the disease.

Eligibility Criteria

Eligibility was restricted to sources that discussed artificial intelligence in relation to occupational health practice. Contributions examining AI or machine-learning methods in workplace health, chronic illness, or accommodation processes were included, as were studies centred on workers or adults with chronic disease in employment settings and analyses of occupational health systems or employment-related technologies. A broad range of evidence types was permitted, including peer-reviewed original studies, systematic reviews, narrative reviews, conceptual papers, authoritative organizational reports, and other scientifically grounded sources relevant to AI in health or occupational practice. Only English-language publications were included. While no strict publication date limits were imposed, the review placed particular emphasis on literature from the past decade to reflect the rapid evolution of AI technologies.

Sources were excluded when they fell outside the scope of occupational medicine or failed to address AI in a meaningful way. This included publications unrelated to workplace health, studies focused exclusively on clinical diagnostic applications without relevance to employment, non-scholarly blog entries lacking identifiable expertise or scientific grounding, conference abstracts without available full texts, and any material published in languages other than English.

Search Strategy

The literature search followed a structured plan and drew on several major academic databases, including PubMed, Web of Science, and ScienceDirect, as well as recognised organizational sources. The search used predefined thematic terms covering areas such as early signs of functional decline, job-related adjustments for chronic illness, the use of wearables in health monitoring, conversational tools relevant to occupational health, and predictive approaches applied to chronic disease. The key search terms and Boolean combinations included: "artificial intelligence" AND "occupational medicine", "AI" AND "workplace accommodation", "machine learning" AND "occupational health surveillance", "chronic illness" AND "workplace" AND "AI", "predictive analytics" AND "worker health needs", and "digital health" AND "return to work".

Study Screening and Selection

Screening began with a review of titles and abstracts, and items unrelated to the topic were excluded at this point. The publications that remained were then read in full to check whether they met the eligibility criteria established for the review.

Data Extraction

Data extraction was performed systematically for each included source. The review gathered information on the type of AI technology examined; the specific occupational health application, such as early needs detection, monitoring, or return-to-work prediction; and the target population or chronic illness context addressed in the study. During extraction, we noted the main results of each study, the advantages reported by the authors, and any methodological or ethical issues they raised. We also recorded how each source related to workplace accommodation or to occupational medicine more broadly. The purpose of this step was to identify the main themes running through the literature and to clarify how the technologies operate, as well as their possible implications for workers' health and ability to function.

Synthesis Approach

A thematic synthesis approach was used to organize and interpret the extracted information, with the analysis structured around the predefined research questions. During this process, the evidence was examined and clustered into four overarching thematic domains: the early identification of worker needs, the use of AI to support workplace accommodation strategies, the benefits and broader opportunities AI offers for occupational medicine, and the risks, limitations, and remaining evidence gaps identified in the literature. This approach supported the inclusion of varied kinds of evidence and helped situate established insights alongside newer developments concerning AI in occupational medicine.

Justification for the Method

A Structured Narrative Review was selected as the most appropriate methodological approach because the existing literature on artificial intelligence in occupational medicine is highly heterogeneous, encompassing empirical studies, technical reports, and conceptual analyses. The field is still developing, and only a small number of AI systems have been tested thoroughly in real workplace conditions. Work in this area spans several disciplines, including occupational health, computer science, ergonomics, and chronic disease management. Because the evidence takes such varied forms, a structured narrative design offers the flexibility needed to examine them together without losing methodological clarity. This approach supports a synthesis that reflects the contextual complexity of the subject and helps clarify both current uses of AI in occupational medicine and possible future directions.

Results

The findings of the Structured Narrative Review are presented in line with the main themes defined at the outset. These include work on the early recognition of support needs, the use of AI in guiding workplace adjustments, discussions of its value for occupational medicine, and the limitations and ethical issues identified in the literature. Together, these themes illustrate both what is currently known and how the role of artificial intelligence in occupational medicine is beginning to develop.

Early Identification of Worker Needs

Across the literature, AI demonstrates significant potential in early detection of health-related needs in workers, especially those living with chronic illnesses [11]. AI tools are able to work with large and varied datasets, drawing on sources such as electronic health records, information from wearable devices [12], and workplace-based monitoring systems [13]. By analysing these combined inputs, they may reveal indications of emerging functional difficulties [14], increasing fatigue [15], musculoskeletal strain, or the worsening of chronic disease [2].

Some monitoring systems use machine-learning components built into sensors and wearable devices [14], which makes it possible to observe changes in a worker's condition over time [16]. By setting new measurements against a person's usual patterns, these systems can draw attention to changes in posture, activity, or physiology that arise before they would typically be recognised in clinical evaluation [17]. A number of studies have contrasted such continuous, AI-supported monitoring with the periodic assessments used in standard occupational practice [2, 18].

Various predictive approaches—among them neural networks, support vector machines, and random-forest models—have been applied to estimate injury risk, return-to-work patterns, and disability-related outcomes [2]. Their performance differs substantially across studies, which points both to the promise of these techniques and to persistent methodological issues [19, 20].

Overall, studies reported that AI systems detected indicators of functional decline earlier than traditional assessment methods [2, 14]. Across studies, fatigue detection and musculoskeletal strain monitoring were the most frequently evaluated AI applications.

AI-Supported Workplace Accommodation for Chronic Illness

Several publications have explored how AI-based systems can inform individualized workplace adjustments [21, 22]. Some decision-support tools bring together information on workers' health status, job-specific ergonomic requirements [14], and data from real-time monitoring systems [23]. Using these inputs, the systems propose accommodation options that may include changes in workload, ergonomic modification, task rotation, or adjustments to scheduling [11].

Digital tools, including mobile health applications and conversational agents [24, 25], offer additional support for workers with chronic illnesses. Some applications track symptoms over time [26], others provide guidance on self-management strategies [27], and several can notify occupational health staff when signs of functional decline appear [28]. While these tools are well established in clinical care for chronic diseases such as diabetes [29], their specific value in workplace settings has received limited investigation [30].

AI also contributes to accommodation planning through improved assessment of functional capacity [31] and prognostic predictions [32]. These capabilities may help clinicians determine appropriate modifications that preserve work ability [33].

Across the reviewed studies, AI systems generated individualized recommendations informed by real-time functional data [5].

Benefits and Opportunities for Occupational Medicine Practice

The review points to a number of areas in which AI may offer practical value for occupational medicine. One example is the use of systems that combine continuous information on workers' health, ergonomic exposures, and environmental conditions. Using these combined inputs, they may highlight risks at an earlier stage than is usually possible with periodic assessments [34, 35, 36]. It also improves diagnostic and assessment capabilities, particularly through AI-assisted image analysis and pattern-recognition tools that support earlier detection of occupational diseases such as pneumoconiosis [37, 38, 39].

Beyond clinical applications, AI can increase efficiency [40] and reduce administrative burden [41] by automating documentation [42], triage, and routine screening tasks [27], thereby allowing occupational health professionals to devote more time to complex decision-making [43].

Some studies used AI-derived functional assessments or prognostic information to inform accommodation planning [44]. When information on workers' characteristics, functional capacity [45], and real-time monitoring data [31] is analysed together, AI systems can propose accommodations that are better matched to individual needs and may help sustain long-term participation in work [11], including for people managing chronic conditions [46].

Predictive approaches built on AI also contribute to return-to-work decisions [47]. They have been used to estimate likely recovery periods [48], to suggest suitable temporary or modified tasks [49], and to inform plans for safe and personalised reintegration [50].

Limitations, Ethical Concerns, and Evidence Gaps

Although the literature describes a number of promising applications, important constraints continue to shape the use of AI in occupational medicine. Many tools are still at the prototype or pilot stage [51], and only a limited subset has been examined in varied workplace settings [52] or in studies involving large worker cohorts [53]. Consequently, real-world evidence on effectiveness and broader applicability remains scarce [54].

Concerns about data quality and representativeness also persist. Occupational datasets may be incomplete, inconsistent, or built on narrow samples that under-represent minority [55] or otherwise vulnerable groups [56], creating conditions in which algorithmic errors and biased classifications are more likely to occur [57].

Ethical questions were raised repeatedly in the reviewed studies. Because AI methods draw extensively on sensitive health and employment information [13], issues related to consent, autonomy, and data stewardship remain central [58, 59]. In addition, many models function as opaque systems [13], which makes their reasoning difficult to interpret and can erode trust among clinicians and workers [60]. Limited explainability is particularly problematic when AI outputs are used to inform fitness-for-work judgments or accommodation planning [52, 61].

Implementation challenges are also significant. Effective adoption requires alignment with workplace infrastructure, regulatory frameworks, and clinical workflows [3]; without this, AI tools may fail to function as intended [62]. Additional research gaps persist, including the need for standardized evaluation frameworks [63], explainable and equitable AI models [61], and longitudinal, workplace-based validation studies [64, 65]. Several studies recommended interdisciplinary collaboration between occupational health, data science, ergonomics, and public health [3, 66].

Table 1. Summary of Main Themes Identified in the Structured Narrative Review

Theme	Key AI Applications	Potential Benefits	Limitations / Challenges
1. Early Needs Detection	Wearable sensors and digital monitoring [14, 17]; machine-learning risk prediction models [23; 2]; pattern-recognition tools for functional decline [3]	Identifying the first indications of reduced functional capacity [14]; picking up early markers of fatigue or strain on the musculoskeletal system [15]; supporting timely action so symptoms do not worsen [16]	Data variability and inconsistent sensor accuracy [17]; need for validated workplace datasets [23]; limited real-world testing [2]
2. Workplace Accommodation	Decision-support systems for ergonomic adjustment [14, 22], AI-guided workload/task adaptation [11]; integrated health-workload models [31]	Personalized and dynamic accommodation plans [5]; improved job retention for chronic illness populations [21]; real-time adaptation to functional changes [23]	Absence of agreed evaluation or implementation frameworks [33]; minimal linkage between AI tools and employers' existing systems [11]; marked differences in how organisations and industries put these tools into practice [22]
3. Chronic Disease Self-Management	Use of conversational systems to assist with symptom reporting and day-to-day management [24; 26]; mobile health applications that incorporate predictive functions to guide users [67]; platforms that provide ongoing monitoring for individuals with chronic conditions [25]	Better adherence to treatment plans and improved self-management behaviours [67]; earlier recognition of symptom worsening or flare-ups [24]; more consistent observation of health status outside formal clinical encounters [26]	Privacy concerns and data-sharing risks [30]; need for digital literacy [25]; limited workplace-specific validation [45]
4. Monitoring and Prediction	Systems using IoT technologies to monitor workers' status continuously [34]; predictive approaches applied to injury risk or return-to-work forecasting [51; 50]; machine-learning models developed for prognostic estimation in occupational contexts [47; 48]	Clearer identification of situations or conditions associated with elevated risk [34]; better-informed planning for return-to-work processes [47]; prevention strategies that can be directed toward specific worker needs or risk profiles [51]	Overfitting and inconsistent performance across populations [50; 47]; limited diversity in training data [51]; explainability concerns [48]
5. Barriers, Ethical Concerns & Evidence Gaps	Frameworks that regulate how worker data are collected, stored, and accessed [13]; mechanisms that allow auditing and clearer inspection of model behaviour [59]; development practices aimed at reducing unequal performance across worker groups [55]	Greater confidence in AI-supported decisions and safer use of these tools when ethical protections are in place [68]	Handling of sensitive worker data brings GDPR obligations that must be observed [13]; employers could use AI outputs in ways that are intrusive or inconsistent with their intended purpose [53]; evidence remains limited on how these systems perform in day-to-day workplace conditions [55]

Summary of Findings

Overall, the included studies examined AI applications for detecting health-related needs and describing approaches to workplace accommodation [3, 11, 67]. Reported applications included continuous monitoring, personalized recommendations, and decision-support systems [2, 3, 11, 51]. Several studies noted methodological, ethical, and practical constraints. [2, 3, 61].

Discussion

This review considered the ways in which artificial intelligence (AI) is being used to identify worker needs at an early stage and to inform workplace accommodations for people with chronic illnesses. The studies reviewed point to a number of potential applications, but the evidence remains uneven and continues to evolve. The next parts of this section examine these results in relation to occupational medicine, highlighting practical relevance, methodological issues, and questions that warrant additional research.

AI as a Tool for Early, Proactive Occupational Medicine Intervention

AI has the potential to move occupational health from periodic, retrospective assessment toward continuous and proactive monitoring. This shift is important because earlier identification of functional decline could allow clinicians to intervene before symptoms escalate or impact work ability [2, 11, 51]. However, the readiness of existing AI tools for routine workplace use is limited. Many reported models are built on narrow datasets, making them vulnerable to overfitting and poor generalizability when applied to heterogeneous worker populations [16, 64].

Although predictive algorithms theoretically align with the preventive ethos of occupational medicine, their performance in real-world conditions remains uncertain. The wide range of accuracy reported in studies—especially those modelling return-to-work outcomes—indicates that many systems are not yet sufficiently reliable for decisions that carry legal, ethical, or safety consequences [47, 69, 70]. At this stage, AI outputs are best treated as supplementary information rather than as independent diagnostic or prognostic judgments.

Expanding Opportunities for Personalized Workplace Accommodation

In the context of accommodation, AI appears most useful when it helps clinicians work through decisions that need to be adapted to the circumstances of each worker. When health information is considered together with data on job demands, these systems can assist clinicians in selecting adjustments that align with changes in a worker's functional capacity [11, 21]. For chronic conditions that fluctuate over time—common in autoimmune, metabolic, and respiratory disorders—an individually tailored approach can help avoid overly restrictive measures while still supporting sustained participation in work.

However, most evidence supporting AI-driven personalization comes from clinical disease management rather than workplace settings [53, 71]. Introducing these systems into workplace settings will depend on testing them in different sectors, establishing practical guidance on how employers should apply their recommendations, and putting in place measures that prevent personalised adjustments from turning into additional monitoring or expectations placed on workers. Thus, while the conceptual value of personalized accommodation is strong, its feasibility remains insufficiently demonstrated.

Benefits for Occupational Medicine Practice

Findings from several studies indicate that AI may reduce routine administrative work and improve the sorting of clinical or occupational health cases, as well as support more accurate assessments. These gains could allow clinicians to devote more attention to complex judgments, including fitness-for-work evaluations and long-term accommodation planning [41, 43, 72]. AI-enabled imaging and pattern-recognition tools also offer earlier detection of occupational diseases (e.g., pneumoconiosis), which could improve surveillance in high-risk sectors [73, 74].

For the potential benefits to materialise, organisations must be ready to work with these technologies. If the tools do not fit into routine processes, if staff are unfamiliar with them, or if the interfaces prove cumbersome, AI can end up complicating tasks instead of simplifying them. In practice, the value of AI depends not only on what the technology can do but also on how organisations structure and oversee its use. Without supportive systems, even strong technical capability has limited impact.

Limitations in Current Evidence and Real-World Applicability

A recurring issue in the literature is the distance between findings generated in controlled settings and the realities of day-to-day workplaces. Many AI models are developed using clinical or simulated datasets that do not capture the range of conditions present in occupational environments, which restricts their external validity [75, 76]. In addition, the absence of large, representative occupational cohorts restricts the development of robust and equitable models [55, 77].

Another methodological concern is inconsistent reporting: studies vary widely in predictor selection, outcome definitions, and validation methods, making comparisons difficult. In occupational medicine, where assessments may influence employment outcomes, the variability in current evidence highlights the importance of developing evaluation frameworks that are specifically designed for workplace use [61, 63].

Ethical and Governance Challenges

Occupational settings amplify ethical risks because AI systems intersect with employment, health status, and power asymmetries between workers and employers. The ethical challenges identified in the literature can be grouped into four interrelated but distinct domains: privacy and data protection, algorithmic fairness, explainability and transparency, and risks of misuse or harmful deployment.

Privacy and Data Protection

Many of these systems depend on detailed physiological, behavioural, and symptom data from workers. Accessing and processing this type of information raises issues about how consent is obtained, how autonomy is preserved, and whether GDPR safeguards are fully met [10, 58, 78].

In settings where employment and job security may be affected, consent may not be entirely voluntary, making it necessary to impose strict controls on who can access the data, how long it is stored, and whether it can be used for purposes beyond the original intention.

Algorithmic Fairness and Equity Risks

Bias in training datasets may lead to systematically poorer model performance for minority, older, precariously employed, or medically complex workers [55, 57, 66].

Such inequities could inadvertently reinforce existing disparities in exposure risk, disability recognition, or return-to-work outcomes. Reducing these risks depends on using datasets that accurately reflect the diversity of the workforce and on evaluating models for biased patterns, together with design choices that prioritise fairness so that vulnerable groups are not placed at a disadvantage.

Explainability and Transparency

Many AI models function as opaque “black-box” systems, limiting the ability of clinicians and workers to understand or challenge decisions affecting fitness for work or accommodations [60, 79].

Low explainability undermines trust, complicates clinical accountability, and conflicts with occupational medicine’s requirement for transparent, defensible reasoning in decisions that may affect employability or legal rights. Explainable AI (XAI) approaches are therefore essential for safe deployment.

Risk of Misuse and Power Asymmetries

AI-generated information can be misread or redirected toward managerial surveillance, productivity tracking, or decisions about task allocation, work restrictions, or even dismissal—outcomes that may conflict with the clinical purpose of these tools and may expose workers to harm [52, 80]. These risks are heightened in workplaces where employees have little scope to question or contest automated decisions.

Effective use of AI in such settings depends on firm governance arrangements: boundaries that restrict permissible uses of AI outputs, protections that safeguard workers’ rights, and oversight that can intervene when practices drift from agreed standards.

Taken together, these issues show that ethical governance is not an optional add-on but a central condition for integrating AI responsibly into occupational health. Meeting these obligations will require more than technical solutions; coordinated research and policy efforts are also needed, as discussed in the next section.

Future Directions and Implications for Occupational Medicine

Further development will require shifting AI work toward the conditions found in actual workplaces. This involves building larger and more representative longitudinal datasets, carrying out validation studies in real occupational settings, and creating explainable systems that clinicians can use to support—rather than substitute for—their own judgement [2, 65].

More research is necessary to see how these systems function within real occupational health workflows, including whether the accommodations they propose can be carried out within existing legal and organizational limits [81]. Moving forward will require coordinated input from technologists and occupational health experts so that technological solutions align with workplace realities [66].

Limitations of This Review

Many studies focus on early-stage tools that have not been examined in real work settings, which means their practical usefulness is still open to question [51]. Added differences in methodological approach and reporting style make comparisons between studies difficult. Limiting the search to English publications may have excluded pertinent studies, and given how quickly AI is evolving, more recent applications may fall outside the review period.

Alignment with Core Functions of Occupational Medicine

When considered in relation to the main responsibilities of occupational medicine—prevention, surveillance, accommodation, disability management, and return-to-work—current evidence suggests that AI may add value in several areas. Continuous data streams can strengthen preventive and surveillance activities, while personalised guidance offers support for accommodation. Predictive approaches also show potential for improving decisions related to disability management and return-to-work planning [3, 11].

These possibilities must still be anchored in strong governance, adequate validation, and practices that uphold worker-centred principles, so that AI contributes to, rather than detracts from, occupational health goals [52].

The practical and policy implications of these findings are outlined in Table 2.

Table 2. Implications for Practice and Policy

Domain	Implications for Occupational Medicine Practice	Implications for Policy and Governance
1. Early Needs Detection	Integrate AI-based monitoring tools (wearables, sensors, predictive analytics) into routine health surveillance to identify emerging functional limitations earlier [7, 15, 14].	Establish regulations for ethical integration of worker health data, ensuring compliance with GDPR and preventing misuse [61, 78].
2. Workplace Accommodation	Use AI-supported decision systems to personalize ergonomic adjustments, task modification, and flexible scheduling for workers with chronic conditions [21, 22].	Encourage national guidelines on AI-supported workplace accommodations, promoting equity across industries and job types [11, 53].
3. Chronic Disease Self-Management	Implement AI-driven mobile health tools and conversational agents to support continuous disease monitoring and adherence for chronic illness in the workplace [67, 25, 24].	Incentivize adoption of evidence-based digital health systems that protect worker autonomy and confidentiality [30, 10].

Domain	Implications for Occupational Medicine Practice	Implications for Policy and Governance
4. Monitoring and Prediction	Use predictive approaches to estimate injury risk and likely return-to-work paths, giving clinicians a basis for earlier planning of appropriate interventions [51, 82].	Standards for validating predictive tools in employment-related decisions are also needed to ensure transparent and equitable model performance [70, 65].
5. Data Quality and Infrastructure	Strengthen data-collection practices so that occupational health datasets are more consistent, representative, and reliable [77, 20].	Develop secure digital systems that allow employers, occupational physicians, and healthcare providers to exchange information safely [78, 36].
6. Ethical and Privacy Considerations	Ensure that ethical safeguards are in place for data access, informed consent, and communication with workers [58, 10].	Regulatory measures are also needed to address transparency of algorithmic systems, reduce the risk of biased outputs, and protect workers from inappropriate digital monitoring [61, 66].
7. Workforce and Organizational Readiness	Provide training for occupational medicine professionals on interpreting AI outputs and integrating them into clinical decisions [72, 52].	Support national workforce development programs focused on digital skills and safe adoption of AI in occupational settings [83, 84].
8. Research and Evaluation	Carry out studies in actual workplace settings to assess how AI tools perform under real conditions and among varied worker groups [51, 53].	Support multidisciplinary research initiatives and ensure that AI performance in occupational contexts is reported openly and in sufficient detail [2, 65].
9. Equity and Inclusion	Use AI to identify unmet needs among vulnerable worker groups, improving targeted accommodation strategies [55, 56].	Implement policies ensuring AI tools do not disadvantage older workers, people with disabilities, or workers with chronic illnesses [57, 66].
10. Strategic Integration	Use AI systems in ways that supplement clinical decision-making and respect worker autonomy, rather than substituting for professional judgement [85, 86].	National strategies are also needed to guide responsible AI use in occupational health, ensuring that technological innovation does not override workers' rights [87, 88].

Taking together, these results show that AI offers meaningful possibilities for occupational medicine while also presenting obstacles that need to be addressed. These points are developed further in the Conclusions section.

Conclusions

This review indicates that artificial intelligence is increasingly explored as a means to support early needs detection and workplace accommodation for workers living with chronic illnesses. Current studies describe applications such as continuous monitoring, predictive analytics, and decision-support systems, which have been used to identify potential changes in functional capacity and to inform individualized workplace adjustments [7, 15, 21, 22]. While these applications align conceptually with the preventive and adaptive principles of occupational medicine, the overall evidence remains preliminary.

Most available research is characterized by small samples, heterogeneous study designs, and limited validation in real-world workplace settings [51, 53]. These constraints limit how confidently one can judge the feasibility, accuracy, or real-world value of current systems. Ethical issues—ranging from data-privacy obligations to the opacity of many algorithms and the potential for inappropriate use — underscore the importance of strong oversight when AI is applied in occupational settings [61, 66, 78]. Without rigorous validation and robust safeguards, AI-supported systems may introduce new vulnerabilities rather than mitigate existing ones [52, 84].

The findings point to a role for AI as an adjunct in occupational health practice, provided that current gaps in study design are addressed and that tools are tested under everyday working conditions, with implementation approaches that respect transparency and equity. Further development will require input from multiple fields, stronger regulatory direction, and ongoing evaluation to understand which workers and which settings can benefit from AI-supported approaches.

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