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AI in Occupational Health: An Exposure–Disease Pathway Review

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Abstract: This systematic literature review investigates the change AI technologies bring in the anticipation of work-related diseases through relevant monitoring, disease prediction, and intervention analytics within the exposure-disease pathway framework. The review is based on 18 selected peer-reviewed articles and conference papers, explaining how AI-driven technologies, such as sensors, wearables, and high-throughput omics, can enable real-time hazard detection and risk assessment. Furthermore, the review underscores AI's potential in driving personalized intervention strategies, and highlights significant methodological innovations, while emphasizing the challenges in dealing with psychosocial risks and vulnerabilities. Altogether, the findings advocate changing occupational health and safety practices concerning disease prevention forward to improve occupational health and safety, guiding ways for further research and more precise regulatory recommendations.

***Index Terms* – AI-based Occupational Health,AI-based Occupational Disease Prevention,Exposure-Disease Pathway,Wearable Sensors,Personalized Intervention Strategies.**

I. Introduction

Occupational health concerns have been a challenge to workplace safety and public health for a substantial period of time. Historically, preventative strategies which are often proactive and reactive, are based on peripheral evaluations of periodic checklists, have struggled to adapt to the rapid changes in work structures and exposure profiles. Recently, the development of Artificial Intelligence (AI) technologies has enabled new transformations to be made in the field of OHS. By implementing AI into detection and preventative measures, exposures can be monitored nowadays in a more continuous approach, risks can be predicted more accurately, and timely interventions can be put into place.

The exposure–disease pathway framework is crucial in actuating this paradigm shift AI is promising to bring. This approach systematically allows the steps towards, and from, exposing hazardous elements with resultant unhealthy conditions to be tracked, enabling one to pinpoint crucial intervention gaps that can be invested into. Several studies documented in AI-enable the monitoring of complicated data systems that could be composed of streams of wearable sensor data, high-throughput omics and network analyses, as well as monitoring processes into predictive models. These collected studies provide a fresh viewpoint on the expansive possibilities of AI in occupational disease preventions (El-Helaly et. al., 2024; Nwanaji-Enwerem et. al., 2021; Aslan et. al., 2023).

II. AI in Exposure Assessment and Monitoring

The potential of Artificial Intelligence (AI) technology to transform existing processes is particularly evident in exposure assessment owing to its use of sensor networks and real-time data. In this context, the work of El Helaly et al. (2024) provides in-depth analysis of the application of AI with wearables, IoT sensors, and smart PPE through the development of systems aimed at the automatic and continuous monitoring of workplace risks. In this particular study, the authors highlight the ability of AI systems to detect environmental parameters to identify the onset of possible risks, thus enabling proactive action to be taken.

In the same way, Aslan et al. (2023) have presented a comprehensive analysis of AI in relation to OHS from hazard identification to even the automation of safety protocols. Their work demonstrates that in real time, driving sensors that are data linked and applying machine learning algorithms can expose data that contains unrecognised hazards. The need to balance human evaluation and AI-sustained observation stems from the primary focus of the study; however, together, these constructs are set to positively alter workplace safety.

These studies remind us, however, that AI technologies in exposure assessment do not just enhance the identifying of physical hazards, but also aid in developing proactive models for occupational health and safety.

III. Predictive Analytics for Risk Assessment

In exploring the AI capabilities literature, one area emphasis the integration of environmental sensors and high-throughput omics systems data to predict disease risks with great accuracy considering the exposure-disease continuum. Nwanaji-Enwerem et. al. 2021 propose a multidisciplinary approach to aging biomarker research by integrating social, chemical, and structural components into a single compound exposome framework. This paper illustrates how multifactorial exposure assessments can be used to predict health outcomes which demand structural inclusivity models for racial disparities, making them much broader.

Goodrich etal. 2023 tell a different story, changing the focus to PFAS contamination and its impact on metabolomics. It has been demonstrated that PFAS alter metabolic pathways, particularly in the processes of tyrosine metabolism and de novo fatty acid biosynthesis. This change is suggested to be one of the many early indicators for cardiometobolic risk, which in turn, would make AI risk prediction more precise.

These predictive techniques are complemented by progress in transcriptomics. For example, in a recent study, blood gene expression profiling was able to demonstrate relationships between immune-related pathways and chronic low back pain, which many individuals experience as an occupational hazard (Vigeland et. Al, 2025). The application of such molecular biomarkers to AI algorithms is crucial for risk stratification at an early stage.

Almomani et. al. (2023) provides evidence of contemporary differentiating painful and painless neuropathies through profiling sodium channel gene variants. These genetic markers are used to explain the granularity of nociceptive pathways and together with the data on exposure to the environment, they may improve the AI system's predictive performance.

Research on response to vascular risk factors or toxins is aberrant when compared to the genetic and metabolic aspects, but it is necessary in order to build a comprehensive predictive model. Shi et. al. (2021) demonstrates that arsenic exposure causes a certain dose and time of ATF3 in human bronchial epithelial cells through JNK and p38 pathways. Rodríguez-Sánchez et. al. (2022) focuses on how ozone modifies hypothalamic signaling and what it means for metabolic responses under toxic stress. Lastly, Santos et. al. (2023) employs a systems biology approach to examine the influence of environmental toxins such as benzene and malathion by describing hub genes and interaction pathways which act as biomarkers.

The studies highlight how AI-based predictive models may be effective in predicting the onset of a workplace illness by integrating complex data such as metabolomics and genomics before there are any clinical symptoms.

IV. AI-Driven Intervention Strategies

Following the identification of possible hazards by means of predictive analytics, the next most important step is intervention. Formulation of personalized intervention strategies based on the particular AI driven decision support systems have emerged as great tools for individual risk profiles.

Mallet et al. (2023) describe the cancer chemoprevention effects of bioactive compounds in their study with the focus on the impact of the polyphenolic mixture released during the fermentation of blueberries on the cancer stem cell features. Even though this research deals with mammary carcinoma, its methodology illustrates how AI would be used to enhance chemoprevention with regard to specific occupational exposures by modifying AI interventions to such exposures.

Simultaneously, Veyhe et. al. (2024) advances research on chronic lymphocytic leukemia (CLL) and uses molecular profiling to assess how patients respond to treatment while receiving ibrutinib therapy. The patients' outcomes from the study on clonal stability and genomic progression is vital towards constructing AI enabled therapeutic decision-making systems, particularly in developing modulatory strategies for intricate molecular systems.

The work of Ryan et. al. in 2024 further demonstrates potential therapeutic targeting of particular biochemical pathways with the example of using a ferroptosis inhibitor to reduce oxidative damage and improve functional recovery after spinal cord injury (SCI). Their work emphasizes the need for timely intervention considering the SCI is not typically classified as an occupational disease, but the logic AI-augmented intervention methodologies in occupational health systems (OHS) take is firmly rooted in the ability to modulate specific pathways to halt or even reverse disease progression.

These examples serve to illustrate the notion that AI can not only anticipate health risks, but design and implanted tailored intervention plans that shift the focus of occupational health from a passive to an active, individualized nature.

V. Advancing the Surveillance of Occupational Health

The continuous integration of data streams obtained from discrete and heterogeneous worker-based health monitoring systems determines the effectiveness of surveillance in occupational health. Analytical methods featuring high-frequency and high-throughput processing when combined with AI can detect early signs of adverse health concerns.

Within the literature discussed, there is a predominant emphasis on predictive modeling and intervention, that indirectly highlights the potential for enhanced surveillance. For instance, molecular and transcriptomic investigations like those of Vigeland et al. (2025) and Almomani et al. (2023) show that high resolution biomarker profiling can provide signals indicative of adverse occupational outcomes. Coupling these methods with real time sensor data as discussed by El-Helaly et al., (2024), Aslan et al., (2023) creates a continuous framework for the surveillance of occupational health.

In addition, network-focused methods like those employed by Santos et. al. (2023) enables the conversion of intricate molecular interactions into usable data. These examinations can be further developed for real-time observational cases, wherein an AI evaluates changes from the standard health metrics on a continuous basis. While none of the publications reviewed here incorporate the concepts of Natural Language Processing (NLP) or flagging anomalies in reported incidents, the sophisticated techniques mentioned give instructions on how to build the integrated systems for monitoring and surveillance that would fetch data from multiple sources using a single password protected control system.

VI. Advancing the Surveillance of Occupational Health

The prevention and management of psychosocial risks is a growing aspect of occupational health, which, for some regions, is still at the emerging stages. Psychosocial risks, such as stress and burnout, can be particularly detrimental to one's health. To our surprise, the current collection of publications indicates that there is a lack of direct engagement with these risk factors. None of the studies have employed sentiment analysis or workload monitoring with an artificial intelligence (AI) component.

Such a gap is revealing in itself. The strong emphasis on physiological, biochemical, and molecular markers in the literature fuels a research gap in the development of AI systems capable of integrating psychosocial markers of occupational exposure. Addressing such a gap will enable research endeavors that harness AI not only to capture environmental and molecular markers but also the psychosocial factors of the employees.

VII. Advancing the Surveillance of Occupational Health

With respect to AI methods, some studies go beyond the primary researches and analyze the presence and absence of exposure–disease relationship in greater detail than it is defined within the confines of an occupational context.

Cui et. al. (2021) provides an analysis of molecular signaling in chronic lymphocytic leukemia (CLL) and describes some pathways that could, in a broader sense, assist in the design of AI surveillance and intervention systems for occupational environments. Tanksley et. al. (2023) analyzes the interaction between incarceration history and cognitive impairment as a consequence of genetic risk. While this study resides outside the bounds of traditional occupational health, it helps in appreciating how different risk factors may be posed by different forms of exposure towards the attainment of some negative health outcomes over time.

This is also the case for Morey et. al. (2022), who conducted transcriptomic research on common bottlenose dolphins And while the research does not pertain directly to the wildlife aspect, the design for the study, which uses high-throughput RNA sequencing to measure changes in immune system components and cytoskeletal associated molecules, has a resemblance to the sophisticated systems formidable to human occupational health.

Fassio et. al. (2023) makes the connection between the activity of inflammatory cytokines and the mechanisms of osteoimmunology in spondyloarthritis, which include bone remodeling. Although these findings are decidedly clinical, they may provide a surrogate for monitoring musculoskeletal disorders in specific working populations. Thor et. al. (2022) examines the response of Arctic copepods to ocean acidification from a metabolic perspective. While their findings on changes in energy metabolism are ecological in nature, they underscore, and serve as a model for, the metabolism changes as studied in human research and comparison of adaptive responses.

The blood transcriptome profiling in Myotonic Dystrophy Type 1 (DM1) conducted by Nieuwenhuis et. al. (2022) adds to the example of molecular surveillance using high-throughput technology. While DM1 does not qualify as an occupational disease, the severity of immune dysregulation and its link to disease outcome suggests that the same surveillance approaches may be adopted for occupational disease cases.

The case studies as presented illustrate the many possibilities of the exposure–disease paradigm and the many ways that AI can process findings from different fields and construct strategic plans for occupational health.

VIII. Future Directions and Research Opportunities

Research opportunities from the study results can be summed up in a few promising directions. One of these is the refinement of AI algorithms to enable integration of data from various levels, such as sensor/wearable networks to high-throughput omics and network analysis.

Aslan et. al. (2023) and El-Helaly et. al. (2024) recommends stronger AI and OHS practitioner partnerships by providing effective policy and training scope. As suggested by Nwanaji-Enwerem et. al. (2021) and Goodrich et. al. (2023), there is a need for more inclusive methods to tackle the problem of measuring complex exposure profiles due to many environmental and social determinants.

Some of these challenges were addressed using AI treatment strategies by Mallet et. al. (2023), Veyhe et. al. (2024), and Ryan et. al. (2024) who showed the promise of AI guided interventions. However, such interventions highlighted algorithmic challenges in timing of treatment or the persistence of molecular difficulties over time. In Section 6, the lack of consideration of psychosocial risk factors emphasizes another gap in the literature that requires more attention. Emotion recognition in real time or during work tasks combined with traditional biomarker monitoring would provide a broader picture of health among the workers.

The proposed future directions stem from current research activities and are not self-contained. AI's advancement in occupational health likely rests on incremental progress in data harvesting, model enhancement, and cross-discipline integration, which is arguably well aided by the varied researches in our review.

IX. Conclusion

The papers which comprise our chosen AI literature reflect a narrative which is disproportianley evolving compared to its current state. The merger of artificial intelligence within the realm of continuous monitoring systems (El-Helaly et. al., 2024; Aslan et. al., 2023), is believed to have a concrete measurable opportunity in the domain of exposure evaluation. At the same time, the whole figure of predictive modelling is undergoing a recognisable transformation with the addition of high-throughput omics plus network analysis (Nwanaji-Enwerem et. al., 2021; Goodrich et. al., 2023; Santos et. al., 2023). There is, indeed, promising case study intervention strategies (Mallet et. al., 2023; Veyhe et. al., 2024; Ryan et. al., 2024) that pragmatically demonstrate the shift of occupational health and AI from being reactive to proactive systems.

Nevertheless, an intriguing gap stems from the understanding: the lack of literature in AI-driven monitoring and mitigation of psychosocial risks is surprisingly low. holistic appreciation mandating AI systems which cover the bifocal aspect of workplace wellbeing - physical and mental health - invite further research.

The combination of these studies underlines the possibilities of AI in occupational health. With the advancement of exposure assessment, monitoring tracking, AI predictive modeling, and individualized intervention programs, we are likely to witness a new frontier in proactive prevention of occupational medical diseases. Such changes are likely to optimally improve not only the safety and health conditions in workplaces but the general health of the population as well.

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