Job exposure matrices for use in respiratory health in low- and middle-income countries: A commentary on relevance and future direction

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Abstract

Occupational exposures are critical yet often overlooked contributors to chronic respiratory disease. Job Exposure Matrices (JEMs) are widely used to assign occupational exposures where direct measurement is not feasible, particularly in large epidemiological studies. However, their applicability in low- and middle-income countries (LMICs) is limited by contextual, structural, and methodological challenges. Drawing on insights from a focus group of occupational respiratory health and exposure assessment experts, this commentary examines key limitations in applying existing JEMs to LMIC contexts including high prevalence of informal employment, job variability, and higher exposure levels. The group identified priority areas for future refinement, including temporal and geographical calibration, and integration of mixed-role employment. While JEMs remain the most practical approach for large-scale exposure assessment, their contextual adaptation is essential to ensure valid exposure–response estimation, improve disease burden attribution, and promote greater equity in global occupational health research.

Keywords: Chronic respiratory diseases, Occupational exposures, LMIC, Job exposure matrix

Introduction

Occupational exposures are often overlooked yet critical risk factors for chronic respiratory diseases, contributing to a significant and preventable global disease burden. In high-income countries (HICs), epidemiological tools such as Job Exposure Matrices (JEMs) are widely used to assign estimates of occupational exposures, particularly in large-scale, community-based studies where direct exposure measurements are not available. Low- and middle-income countries (LMICs) experience a disproportionate burden of occupational diseases driven by higher and more heterogeneous exposures, widespread of informal employment, and limited capture of occupational exposures in existing data (Quintero Santofimio et al. 2024). Meanwhile, JEMs developed in HICs are increasingly applied in global epidemiological studies without adequate contextual validation, raising concerns about exposure misclassification and underestimation of disease burden. In this commentary, we examine the relevance and limitations of JEMs for use in LMICs, drawing on insights and discussions of an expert focus group in order to outline priorities for future development. Exposures such as vapours, gases, dusts, and fumes, silica, asbestos, and pesticides, can both cause and exacerbate, chronic respiratory diseases including asthma, chronic obstructive pulmonary disease (COPD), and pneumoconiosis (Blanc et al. 2019). Recent evidence also suggests that earlier subclinical signs such as small airways obstruction may already be linked to these exposures (Feary et al. 2023; Quintero-Santofimio et al. 2024). The burden of occupational respiratory disease disproportionately affects LMICs, where reliance on manual labour, limited automation, weak regulation, and large informal sectors may result in higher levels of exposure to harmful agents. Rapid economic transitions and outsourcing of hazardous work from HICs may further increase risks (Jeebhay 2020).

Workplace exposures can be assessed using self-reported questionnaires, expert judgement, objective measurement of inhaled or dermal exposures and biomarkers (Fritschi et al. 1996). Most of these methods require expertise in occupational hygiene and often involve personal sampling to measure individual exposures together with direct observation of workers carrying out tasks at work. These methods are expensive, typically limited to small-scale cross-sectional studies or industrial cohort

settings, are rarely feasible in large community-based research(Sauvé and Friesen 2019). Although new low-cost, portable devices (e.g., particulate matter monitors) offer promise, including in LMICs, large-scale application and the validity of the instruments remain challenging, creating demand for alternative tools to assess occupational exposures such as JEMs.

Job-Exposure Matrices in general population studies

General Population-JEMs (GP-JEMs) typically consist of two axes: a standardized job axis and an agent axis. In the cells made up by the axes (semi-)quantitative estimates of exposure intensity (low, medium, high), sometimes in combination with a probability of exposure can be found (Fig 1). Some GP-JEMs might also incorporate a time axis, considering that exposures tend to decline with time, at least in HICs (Creely et al. 2007) When designed properly, the constructors of a GP-JEMs will have opted for a specific assignment of exposure for a given job (to prevent large numbers of false positive exposed individuals) while some refined quantitative JEM e.g., SYNJEM, have also incorporate a time axis to account for evolving exposure levels (Peters et al. 2016).

JEMs are particularly valuable in community-based or registry-based studies with detailed job histories but which lack direct exposure measurements. By linking standardized job codes, such as the International Standard Classification of Occupations-88 (ISCO-88), to exposure estimates, JEMs allow for broad exposure assignment across large populations. Their key strengths are their low cost, broad applicability, and reduced reliance on self-reported data, which helps minimize recall bias. Importantly, beyond being a methodological tool, JEMs also allow estimation of occupational exposures at the level of the entire working population, making them particularly valuable for public health surveillance and burden of disease estimation, especially in LMICs(Peters et al. 2022).

A previous review by Huntley et al. (2023) (Huntley et al. 2023)identified 33 GP-JEMs, all developed using data from HICs, predominantly in Europe and North America. Several of these were derived from foundational JEMs developed decades ago with some being updated within the las 10 years, including the ALOHA+ JEM (Matheson et al. 2005), Blanc (Blanc et al. 1999), DOM-JEM (Peters et al. 2011), OAsJEM (Kennedy et al. 2000) and FINJEM (Kauppinen et al. 1998). In occupational respiratory research, the ALOHA+ JEM has been applied in over 30 studies to investigate COPD and other respiratory outcomes(De Matteis et al. 2022; Sunyer et al. 1998). Originally developed for the European Community Respiratory Health Survey, it was later extended to include additional exposures such as pesticides, solvents and metals to study neurodegenerative diseases (Matheson et al. 2005). While these tools offer valuable insights, their applicability in LMICs is limited unless they are adjusted for local context, geography, and time.

JEMs do not account for individual-level variation within the same job title, and although this does not lead to bias in the risk estimates (Berkson-error), it does result in loss of precision(Armstrong 1998; Evanoff et al. 2019). In population-based studies, sensitivity is often prioritised over specificity, which may inflate false-positive exposure assignments and biased exposure–response estimates, as most occupational exposures are generally rare (<10%) in the general population (Armstrong 1998) . However, the accuracy of some JEMs can be improved by incorporating individual-level information on tasks and workplace environments. Task Exposure Matrices (TEMs), for instance, can be developed alongside JEMs, to enhance the validity of exposure characterisation and allow for a quantitative assessment. TEMs break down jobs into specific tasks and assign exposure levels to each task, typically using a combination of direct exposure measurements and expert assessment. This approach allows within-job variability to be captured more effectively (Neitzel et al. 2011). However, it will require

detailed information at the individual level on duration and frequency of tasks, which relies on retrospective reporting and may therefore be subject to recall-related exposure misclassification, including non-differential misclassification that reduces the precision of exposure–response estimates and differential misclassification if recall is associated with disease status. Particularly, if datasets are too small, standard errors of the effect estimates become too large, and the broader JEM approach remains preferable (Benke et al. 2000). While these approaches may help reduce information bias, it introduces new challenges related to variability in recall accuracy across different cultural, occupational contexts and long time periods (Le Moual et al. 2018).

JEMs and additional challenges in LMICs

Many GP-JEMs are developed using retrospective data and expert judgment, often without incorporating context-specific information on local occupational practices, industrial processes, or exposure measurements. These tools frequently reflect working conditions in HICs (Huntley et al. 2023), limiting their transferability to LMICs, where work environments, regulatory frameworks (if present), and the nature of informal employment can be substantially different (Quintero Santofimio et al. 2024; Timothy et al. 2022).

In LMICs, accurate exposure assessment can be challenging. Key barriers include limited technical capacity and infrastructure to carry out exposure monitoring, funding constraints, and a shortage of trained occupational hygienists and other occupational health professionals (Quintero Santofimio et al. 2024) In addition, exposure levels can be very high, to the extent that even some standard cost-effective measurement approaches, such as low-cost optical particle counters may not be feasible and should not replace other methods such as gravimetric analysis (Nafees et al. 2021). Therefore, it is essential to contextualize exposure assessment strategies, including direct measurement devices, to ensure accurate exposure measures that in turn will aid to improve the calibration or development of JEMs for LMIC context.

A key consideration when using JEMs is their context dependency. The likelihood and intensity of occupational exposures can vary significantly across countries, regions, industries, and even within the same job title or economic sector, often shaped by factors such as materials used, workplace practices, and regulatory enforcement. For example, a construction worker in a low-resource, less-regulated setting may face significantly greater exposure to respirable crystalline silica or wood dust than a counterpart in a more regulated HIC, due to differences in task automation, protective measures, and enforcement of occupational health and safety standards including occupational exposure limits. A recent scoping review showed that, where exposure assessments had been conducted in LMICs, the levels were significantly higher than equivalent measurements in HICs (Quintero-Santofimio et al. 2024). In many LMIC settings, limited enforcement of occupational exposure limits and reliance on older or poorly maintained technologies contribute to the higher exposure levels. The absence of effective dust suppression or ventilation systems can further contribute to substantially higher exposure levels, particularly in highly prevalent sectors such as construction, mining, and small-scale manufacturing. Another challenge in LMICs is the high prevalence of informal employment, particularly in lower skilled occupations, which hinders accurate exposure attribution and amplifies workers' vulnerability. Many workers engage in seasonal, short-term, or multiple concurrent jobs that are not captured in standardised occupational coding systems. Another challenge is the discrepancy between the occupation (how the worker is hired) and the actual work and tasks performed. Existing JEMs typically assume a single, stable, and well-defined job categorisation, which holds more reliably in HICs or structured cohort studies rather than dynamic, informal labour markets. Compounding this challenge is the lack of findable and accessible data on disaggregated job types and workforce characteristics, which are essential for developing and applying JEMs in LMICs.

Despite these limitations, JEMs have been applied in research based in LMICs. For example, Correa and Santana (2016) used the FINJEM to estimate the number of workers exposed to benzene in Brazil, drawing on data from the national demographic census. They estimated that approximately 8.5% of active workers were potentially exposed to benzene, which was substantially higher than the prevalence reported in Finland (Corrêa and Santana 2016). Job coding in their study was based on ISCO-88 although adjustments by the researchers were required to ensure accurate exposure assignment. While such adjustments can provide one approach, other strategies include country-specific calibration using local exposure data, and task-based refinements. This can help to minimise exposure misclassification and underestimated associations between occupational exposures and health outcomes. Previous studies in HIC have shown that transferring JEMS across settings can result in differences in exposure estimates, reflecting variations in work practices, industrial processes and data used to construct the JEM (Lavoué et al. 2012). International initiatives such as JEMINI have further highlighted both the potential and the substantial challenges of harmonising JEMs across countries, even within relatively comparable occupational and regulatory contexts (Descatha et al. 2019). These limitations are likely to be further amplified in LMICs, where JEMs are often applied using data derived entirely from HIC, increasing exposure misclassification and underestimation of occupational disease burden. Furthermore, while regional initiatives such as the Pan American Health Organization 2015-2025 Action Plan on Workers' Health have sought to promote national JEMs in LMICs, the lack of published outcomes from these efforts highlights the insufficient human and technical capacity of countries to conduct such estimates, and persistent barriers to context-specific adaptation (World Health Organisation (WHO) 2025).

Based on these challenges, we convened a focus group comprised occupational exposure assessment and respiratory health experts to identify key challenges and priorities for applying JEMs in LMIC contexts. The focus group identified several key priority areas for the future refinement of JEMs for LMIC context:

- Temporal calibration: Future JEMs should include variables accounting for historical industrial and occupational trends, regional practices, and evolving technologies. Introducing a time axis would allow for a more accurate reflection of exposures across changing occupational environments, and is relevant to both HICs and LMICs
- Region- or country-specific calibration: wherever feasible, calibration should draw on local data, small-scale exposure studies, and expert input, to improve contextual relevance
- Incorporation of informal and mixed job roles: New models should accommodate informal, seasonal, or mixed-role employment through flexible coding or task-based approaches (e.g. collecting information on time spent on multiple jobs/tasks performed at the same time)

Conclusion

Occupational health research should remain a global priority, as it focuses on modifiable risk factors that can prevent a significant burden of disease especially among those subjected to excessive occupational exposures. Tools such as General Population JEMs must evolve to reflect the diversity of work environments and exposures across the world. Without appropriate adjustment, applying HIC-based JEMs in LMICs risks reinforcing existing gaps and underestimating occupational disease burden in the populations most affected.

It is crucial to develop context-sensitive and methodologically robust adaptations of existing JEMs to LMICs contexts. Efforts to improve exposure assessment in LMICs, and its use for occupational health and safety should be supported through increased funding, cross-country collaboration, and greater

inclusion of LMIC researchers in occupational health research. This is essential not only for informative epidemiological and burden of disease studies in populations with high and under-recognised occupational exposures, but also for advancing global equity in occupational health research and risk mitigation.

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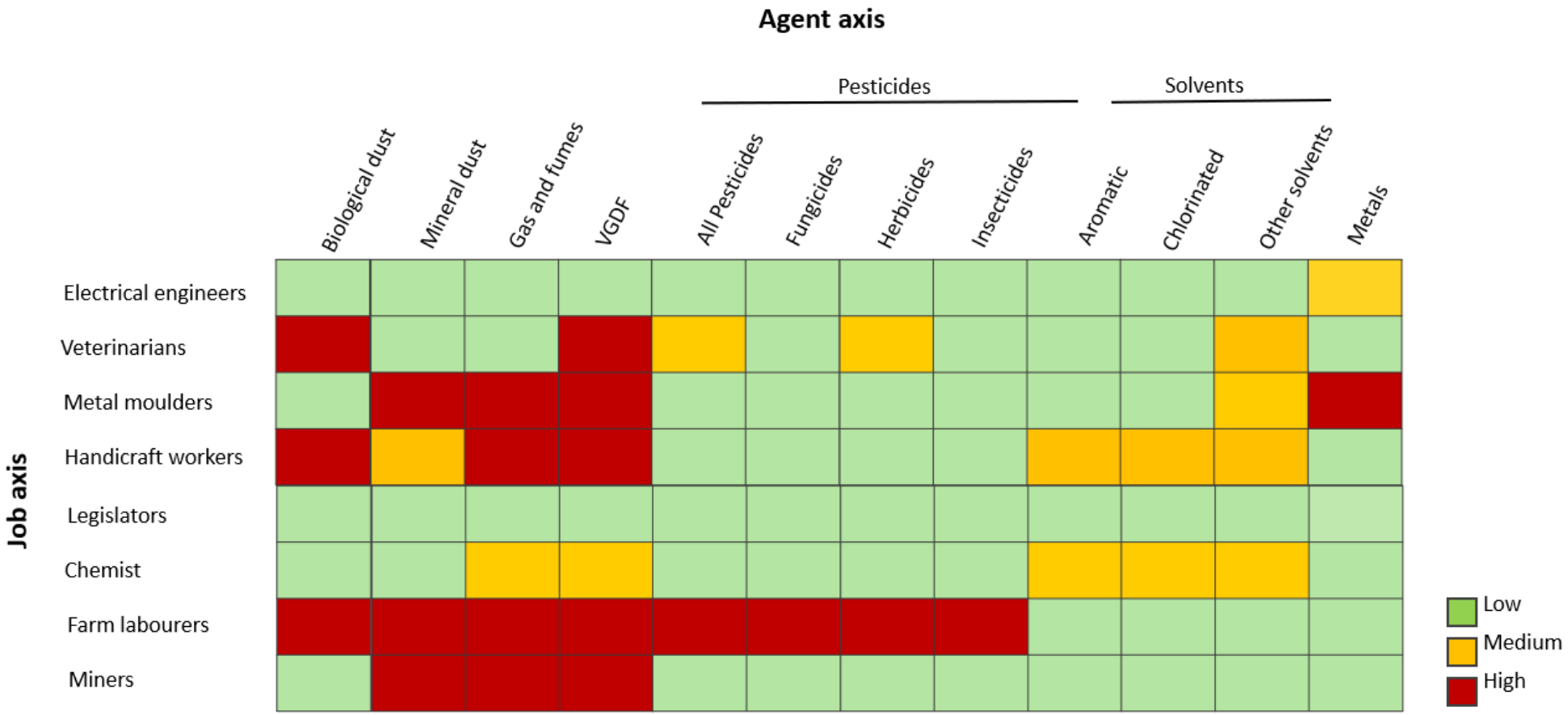
Figures

Fig 1. Schematic representation of the ALOHA+ general-population job exposure matrix (JEM)



The matrix illustrates how exposure levels are assigned for combinations of job titles (rows) and exposure agents (columns). Each cell represents the estimated exposure intensity, colour coded as low (green), medium (yellow), or high (red). This schematic is based on an example of the ALOHA+ JEM. Job titles are coded according to the International Standard Classification of Occupations-88 (ISCO88). VGDF: Vapour, gases, dust and fumes and All Pesticides are composite exposure categories, while all other columns represent individual agents.