Mental health of people in the agricultural sector: insights from massive database in occupational health

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It is known that agricultural workers and farm managers (FM) are exposed to many occupational hazards that make them at risk for health problems, though mental health may not be the first that comes to mind. Indeed, although some studies have highlighted the increased risk of stress, suicide ideation or depression, few of them have comprehensively studied these outcomes using large-scale prospective data and differentiating the variety of jobs and sector in this field.[1]

In this issue of *The Lancet Regional Health—Europe*, P. Petit et al. attempt to fill the gaps on the potential differential risk of depressive syndrome among the French FM population according to different agricultural activities. To do so, they have used data from insurance health databases of the French FM population from 2002 to 2016, performed Cox models and estimated hazard ratios (HR) for depression (defined by combinations of international classification of disease codes (ICD) and antidepressant prescriptions) for 26 agricultural activities.[2] Findings show that cow farming, poultry and rabbit farming, dairy farming, and mixed farming were the activities with the highest risk of depression within the FM population, with HRs ranging from 1.30 to 1.53, while crop farming and unspecified small animal farming had a lower risk, with some differences according to sex.

While there is already evidence on farming activities and poor mental health,[3] the authors highlight that different agricultural activities might have different risk of depression across the entire workforce, suggesting the need to understand precisely the workplace determinants and to establish prevention strategies in these settings. Some risk factors have been suggested, ranging from pesticide to organizational factors.[4–6] However, much research is needed to understand these results, as no information on exposure or organizational factors was available, illustrating the need for complementary approaches to massive administrative dataset.

Indeed, administrative datasets used for claim and insurance purposes might be considered as "Big Data", since they have a massive quantity of data, a high speed of acquisition (velocity), and a variety of data sources (ICD codes and antidepressant prescription), but also have uncertainties regarding data value and the potential for valorisation (the "five V's").[7] As mentioned by the authors, identifying accuracy issues when building the correct algorithm to identify depression cases may arise, as the data were collected for a different specific purpose, requiring a multidisciplinary team with different expertise. Such was the case in this study, where the authors formed a multidisciplinary team with medical, occupational, statistical, and methodological knowledge, which was able to perform a high-quality application and interpretation of the available data.

Moreover, as the authors stated, accurate exposure data were not available in the administrative database, yet the use of job exposure matrices (JEM) may have helped to fill in the gaps. From the relatively simple compilation of subjects' job titles from the administrative data, JEMs would allow more complex information to be inferred by converting coded job titles into exposure estimates.[8] JEMs are usually based on monitoring data, self-reported exposures, expert assessment, or a combination of these methods, and vary widely depending on the type of exposures assessed and the exposure metric applied (e.g., probability, frequency, duration or level of exposure). Many limitations exist, including technical aspects (type of code classification) and non-differential misclassification of estimated individual exposures when assigning the same exposure to all workers in a job.

Confounders were also not well considered due to the limitation of administrative databases, which often do not collect information on health determinants such as smoking, social support, organizational work factors, etc. Enriching administrative databases by adding other environmental, social, behavioral factors through large prospective cohorts has become a major perspective in the field of occupational health.[9] Having such enrichment would allow to have a complete exposome in a life course perspective.[10]

In addition to the important contribution of this study to the knowledge of the mental health of agricultural workers, it has also showed how administrative

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health data can be used as complementary approach to traditional cohort studies, especially in occupational health. New statistical methods combining advanced statistics and artificial intelligence,[11] incorporating the use of massive databases with cohort enrichment, and interpretation by experts from various fields including methodology, epidemiology, medicine and occupational health can broaden the path of research, just like Petit et al. have done in their study. Transcoding the job-classification used in this study may allow the application of JEMs to complement the analyses by Petit et al., and compare them with ongoing cohorts or national surveys assessing health and work determinants.

Contributors

AD and MF initiated the work, AD wrote the initial draft, and MF revised the draft. AD/FD approved the final work.

Declaration of interests

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