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Commentary

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Future Prospects of Occupational Exposure Modelling of Substances in the Context of Time-Resolved Sensor Data

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Abstract

This commentary explores the use of high-resolution data from new, miniature sensors to enrich models that predict exposures to chemical substances in the workplace. To optimally apply these sensors, one can expect an increased need for new models that will facilitate the interpretation and extrapolation of the acquired time-resolved data. We identified three key modelling approaches in the context of sensor data, namely (i) enrichment of existing time-integrated exposure models, (ii) (new) high-resolution (in time and space) empirical models, and (iii) new 'occupational dispersion' models. Each approach was evaluated in terms of their application in research, practice, and for policy purposes. It is expected that substance-specific sensor data will have the potential to transform workplace modelling by re-calibrating, refining, and validating existing (time-integrated) models. An increased shift towards 'sensor-driven' models is expected. It will allow for high-resolution modelling in time and space to identify peak exposures and will be beneficial for more individualized exposure assessment and real-time risk management. New 'occupational dispersion models' such as interpolation, computational fluid dynamic models, and assimilation techniques, together with sensor data, will be specifically useful. These techniques can be applied to develop site-specific concentration maps which calculate personal exposures and mitigate worker exposure through early warning systems, source finding and improved control design and control strategies. Critical development and investment needs for sensor data linked to (new) model development were identified such as (i) the generation of more sensor data with reliable sensor technologies (achieved by improved specificity, sensitivity, and accuracy of sensors), (ii) investing in statistical and new model developments, (iii) ensuring that we comply with privacy and security issues of concern, and (iv) acceptance by relevant target groups (such as employers and employees) and stimulation of these new technologies by policymakers and technology developers.

Keywords: chemical; exposure; models; occupational; real-time; sensor; sensor networks; substances; time-resolved; workplace

Introduction

The maturation of lightweight, miniaturized, and technically advanced (low-cost) sensors has the potential to transform exposure assessment technologies in the occupational setting (AIHA, 2016; National Academy of Sciences, 2017; Morawska *et al.*, 2018). In particular, low-cost miniature sensors that can detect airborne particles and specific (chemical) substances are being developed (hereafter coined 'sensors'). Although larger-sized time-resolved sensor equipment has been used in the workplace for some time now—the scope and application of miniature sensors for assessment of chronic exposures for worker health is expected to widen significantly in the future (AIHA, 2016; National Academy of Sciences, 2017). These new technologies are promising to change the landscape of traditionally used time-integrated sampling methods (e.g. filter measurements for gravimetric and chemical analyses in a laboratory). They also provide a higher sampling resolution in time and space (Negi *et al.*, 2011; Brown *et al.*, 2016) when applied for personal sampling and as a stationary network in the workplace.

Assessment of exposures in the context of worker health can be divided in three broad categories: (i) compliance testing against exposure limits (policy), (ii) evaluation of personal exposures and exposure control systems (practice), and (iii) epidemiological studies (research). All three are aimed at workers' health and disease prevention which receives increasingly more attention in recently introduced concepts such as 'Total Worker Health' [National Institute of Occupational Safety and Health (NIOSH)] and 'Occupational exposome'. Sensor technology could be helpful to fulfil the potential of these concepts and is closely aligned with research on the exposome that promotes a more individualistic and holistic approach to exposure assessment (Wild, 2005). For these purposes, exposure modelling is often based on or combined with exposure measurements, providing exposure assessors with an efficient tool to predict substance exposures of worker populations. With the collection of time-integrated exposure measurements being the norm, the majority of existing exposure models are typically 'static' models that are based on time-integrated measurement data and are able to predict task-based or shift-based exposures of exposure scenarios. This stands in stark contrast with the complexity of workplace exposures when considering the fluctuation of concentrations in time and space and the exposure variability between individuals. High-resolution sensor data provide the opportunity to explicitly take account of changes in concentrations in time and space, and hence new 'dynamic' models are required that can interpret and extrapolate these data. At the same time, it seems inevitable that existing 'static' occupational exposure models will also require significant changes (e.g. re-calibration) to keep up with these new technological innovations and availability of high-resolution data.

This commentary explores the future prospects of exposure modelling in the context of (time-resolved) sensor data. For this purpose, we provide an overview of the possibilities of applying sensor data for occupational exposure modelling purposes, the expected types of newly developed models, their application, their added value, and the critical development needs and challenges in the future.

Opportunities of collecting sensor data for occupational exposure assessment

To evaluate the potential of sensor data for occupational exposure assessment, we drafted an inventory of the current status of time-integrated exposure assessment in relation to time-resolved measurements. From this we identified opportunities and challenges of applying sensors for the measurement of substances, the analysis and characterization of measurement data and new insights for exposure control (Table 1).

When integrating exposure data during a work day of 8 h or an activity of 120 min and we compare that with integrating it every 60 s or even 10 s during that period, it becomes clear why time-resolved sensor data can be considered high-resolution data. The real advantage of higher resolution time-resolved data will be to combine (or synchronize) sensor data with contextual information (from the same resolution) such as activity and location tracking systems (Huang *et al.*, 2010; Negi *et al.*, 2011; Brown *et al.*, 2016) and video monitoring and human activity tracking and recognition (Rosén *et al.*, 2005; Beurskens-Comuth *et al.*, 2011; Lun, 2018;

Table 1. Inventory of traditional sampling versus sampling with new miniature sensors and their (potential) applications.

Traditional sampling	Sampling with new sensors
Measurement (strategy)	
• Limited exposure measurements due to (operational) cost	• Wider sampling possible due to lower (operational) cost (though initial costs for infrastructure and implementation required)
• Task- and shift-based time-integrated exposures	• High-resolution measurements (in time and/or space)
• Insufficient to assess peak exposures	• Insights in peak and short-term exposures
• Samples can be analysed for multiple analytes	• Measurements mostly specific for analyte or substance group
• Recording of mostly observational information (e.g. observation, logbooks)	• Possibility to synchronize the data with real-time 'contextual' information (e.g. location tracking, video)
Data analysis and characterization	
• Limited possibilities to accurately link exposure concentrations with emission sources in time and space	• Possibility to link exposure concentrations with emission sources in time and space
• Variability in exposure often unknown	• Exposure variability can be analysed in detail
• Identify and semi-quantify similarly exposed groups (SEGs)	• More individualized exposure assessment
• Exposure limits are developed and aligned with time-integrated data	• New exposure limits that utilize the variability in time-resolved data will be required
Exposure control	
• Often limited (retrospective) evidence available to design control strategies	• Time-resolved insights for design and evaluation of control measures
• Retrospective feedback only	• Personalized (real-time) digital feedback systems possible

NIOSH, 2018). More individualized exposure assessment can be performed using multiple sensors, as opposed to smaller sample sizes and the similar exposure group approach conventionally used. Exposure levels can be better characterized to provide insights of within- and between-worker exposure variability. It may also be possible to identify emission sources, or pin-point locations and activities related to elevated or peak exposures. This will allow for a more extensive analysis of exposure determinants on an individual level. As occupational exposure limits (OELs) tend to be lowered for substances with chronic effects (e.g. diesel emissions, asbestos), shorter timescale measurements and more individualistic exposure assessments and (real-time) risk management may be a way forward to further reduce workplace exposure levels.

Implications for exposure modelling

New exposure modelling developments are needed if we wish to pursue the use of sensor data. Currently used models vary widely from (i) population or industry-based Job–Exposure Matrices (JEMs) (e.g. Dopart and Friesen, 2017), (ii) empirical (or statistical) models (e.g. Symanski *et al.*, 2006), (iii) mechanistic and semi-empirical models (e.g. Fransman *et al.*, 2011) to (iv) mathematical (or computational) models such as mass balance box models (e.g. Cherrie *et al.*, 2011), transient indoor dispersion models (e.g. Koivisto *et al.*, 2010), and computational fluid dynamic (CFD) models (e.g. Bennett *et al.*, 2018). Most of these models (except transient and CFD models) are 'static' models that predict time-integrated exposures for a job, shift, activity, or location.

We expect three key modelling approaches in the context of sensor data, namely (i) enrichment of existing time-integrated exposure models, (ii) (new) high-resolution empirical models, and (iii) (new) 'occupational dispersion' models.

Enrichment of existing time-integrated models

In the foreseeable future, the existing time-integrated 'static' models (e.g. JEMs, empirical/statistical, mechanistic, computational) are expected to remain practicable for application in practice, research, and policy. One of the reasons for their continued application lies in their relative simplicity and generalizability for a broad spectrum of workplace exposure scenarios. For policy purposes, these models are expected to remain very useful as long as OELs are based on mostly time weighted average (8-h time weighted average exposures. However, a cause of concern is that existing models (in particular for policy) have shown to be inaccurate for certain exposure scenarios which can lead to an underestimation or insufficient control of workers' exposure (Lamb *et al.*, 2015; Riedmann *et al.*, 2015). Using time-resolved sensor data to enrich and refine existing time-integrated models could be an opportunity to increase model accuracy, reduce uncertainty, and enhance reliability.

Mechanistic-type exposure models applied for policy purposes (e.g. the Advanced REACH Tool—ART; Fransman *et al.*, 2011) could benefit from the spatial and temporal information provided by sensor data. One option will be to develop 'exposure profiles' for different activities that provide important information on peak exposures (such as their frequency and duration) and the origin of these peak exposures. For example, an ART activity sub-class 'falling powders' can be refined by making a distinction between specific technologies and work practices (e.g. emptying bags versus emptying a hopper) and sub-tasks (e.g. bag disposal and cleaning). This information could be very informative to build 'exposure profiles' to provide better insights in peak exposures and control options for (amongst other) risk assessment professionals. Another option will be to improve and refine model estimates by using advanced statistical analysis that take account of peak exposures and by re-calibrating these models. At the same time, a critical question that should be considered is whether the enrichment of these existing time-integrated models will significantly improve model performance.

New high-resolution empirical models

Using high-resolution sensor data in data-driven empirical models will enable the linking of relevant sources, activities, exposure circumstances, and locations to exposure levels at a higher resolution in time and space. For instance, these potential exposure determinants can be linked to an exposure level at a certain point in time and even place, whereas when using time-integrated measurement data, they can only be linked to the average concentration during a shift or task. In addition, given the amount of data that can be collected, exposure determinants can be linked to exposure on an individual level.

To evaluate the effects of determinants on time-integrated exposure, which has previously been done for the (further) development of several exposure assessment models (Schinkel *et al.*, 2011; Bekker *et al.*, 2017), regression models are often used. Time-resolved sensor data have unique features that challenge conventional data-analysis techniques. For autocorrelation associated with sequential measurements of time-resolved data, statistical models such as Autoregressive Integrated Moving Average (ARIMA) have been developed (Klein Entink *et al.*, 2011, 2015). However, ARIMA is only suitable for data without long-term trends, thus data in a stationary state, as the model reduces data to a stationary form using differentiation before analysis. If the approximate stationarity of time-resolved data cannot be obtained or the underlying trend is of importance, other inferences or statistical methods are required. Nevertheless, it is possible to combine ARIMA models with regression models to include covariates to investigate exposure determinants of time-resolved data. Also, long-term trends such as decreases in concentration over time, or the study of random effects of between-company and between-worker variance components can be investigated. A limitation is that model parameters cannot vary over time and the models may become complex and convoluted.

More advanced and flexible models will be required that can also accommodate non-stationary series data and non-normally distributed data. Examples include dynamic linear models (Petris *et al.*, 2009; Krone *et al.*, 2018) and state-space models (Durbin and Koopman, 2012). These models can include model parameters that vary over time and allow for the quantification of the relationship between these variables within and between timepoints, as well as the trend and effects within a variable itself. These models can be self-learning to some extent by applying Bayesian analysis where prior knowledge or models can be integrated with new measurements for this purpose. Prior knowledge can be used to add each new data point in time to a model to let the model adjust itself over time (Gelman *et al.*, 2013). When the model is updated one data point at a time, it is in effect self-learning without the need to estimate the whole model again, allowing for fast calculations.

Taking a woodworking shop as an example, a relatively simple sensor-driven model (model 1, Fig. 1a) can be developed using longitudinal regression models (that take account of time) combined with ARIMA. It will be suitable for a specific individual or 'job category' who performs mostly stationary activities with a fixed work protocol, for example a woodworker who is making windowsills every day. This type of model will only require the timeframe of each activity (e.g. sawing, cleaning, sanding) during a working shift together with historic (personal) sensor data. Such a model will be able to forecast personal exposures well in advance (e.g. 3 h) depending on the variability in source emissions. Model forecasts will become more uncertain over time as circumstances at the workstation may change that will influence the exposure, hence not all variability inducing information will be taken into account.

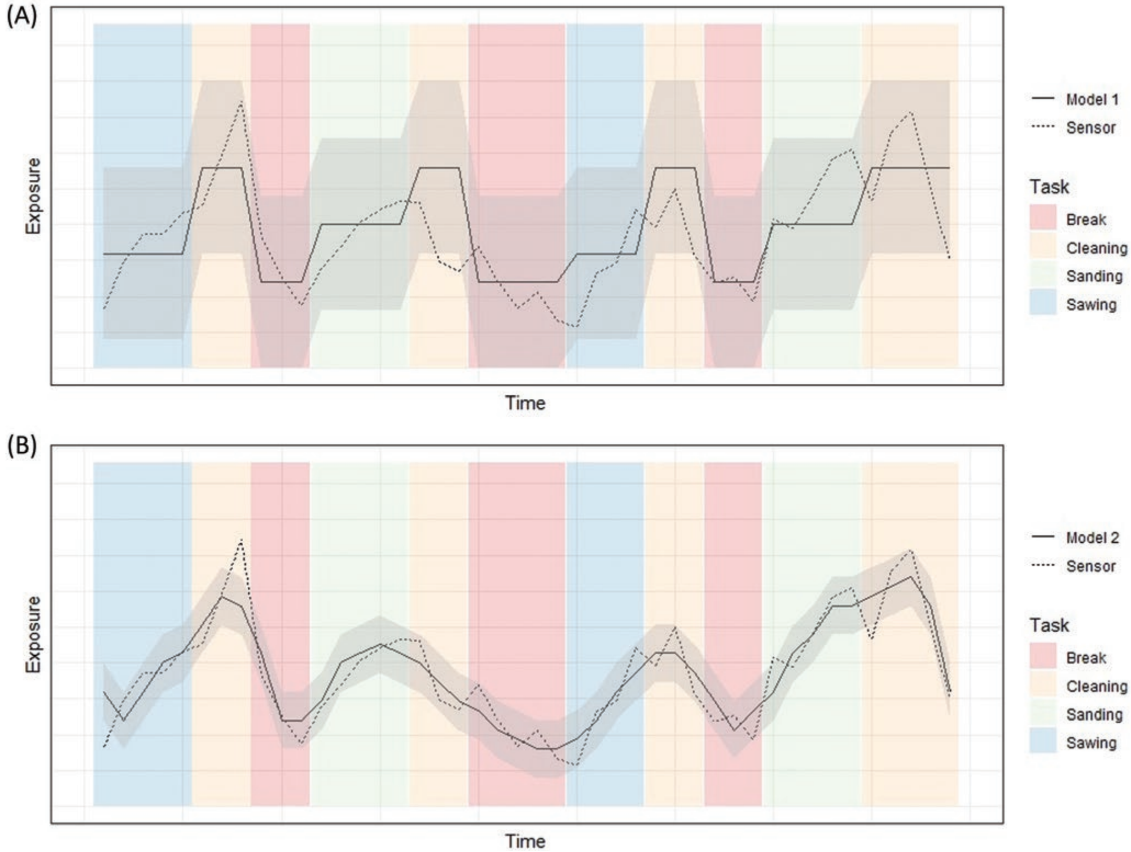

Figure 1. Simulation of two possible sensor-driven models: (a) model 1 using longitudinal regression models combined with ARIMA and (b) model 2 using dynamic linear models. Each model prediction is shown with an uncertainty around the central estimate. A momentary and cumulative exposure estimate can be derived from these model predictions.

More advanced sensor-driven models can be developed using dynamic linear models (model 2, Fig. 1b). This model option will be more complex and will require real-time contextual information that is synchronized with (historic) time-resolved (personal) sensor measurements. The contextual information can for example be obtained from location tracking systems (to track the location of the individual) and smart sensors (e.g. to indicate if local exhaust ventilation is operational or not). Such a model will be suitable for a wood worker with a more random exposure pattern and who works at different locations, involving different tools and equipment and types of wood each day. The uncertainty of model forecasts will be dependent on the accuracy of information acquired regarding the determinants of exposure. There is also an opportunity to further improve such models through self-learning techniques with every new measurement obtained.

As these models may not be ready off-the-shelf models, a learning period should be considered for sensor algorithms and calibration to be refined and to mature.

Such individualized (fit-for-purpose) models could become indispensable in the future for real-time risk management purposes. They could indicate whether a specific activity may be responsible for raising the cumulative exposure above the allowed exposure limit. A spin-off may include the opportunity to link such models with real-time feedback (e.g. 'smart' safety glasses). Feedback systems can give personalized advice to a worker about increased momentary and cumulative exposure levels and preferred control measures for a given activity and emission sources encountered in the workplace.

New 'occupational dispersion' models

Given the possibility to apply personal sensors and stationary sensor networks that are distributed in the work environment, we may expect more cross-pollination of atmospheric dispersion models from the environmental sciences that describe the dispersion of a chemical substance in space. We coin them here in a broader context as 'occupational dispersion models'.

Many single box or multicompartment mass balance models (e.g. Cherrie *et al.*, 2011) have been developed for occupational settings and typically calculate near-field and far-field steady-state average concentration ratios (or general ventilation multipliers) for standard work environments. A more advanced type are transient models that predict dispersion of indoor aerosol concentrations over time (including peak concentrations) at a designated location such as the near-field or far-field of an emission source (Koivisto *et al.*, 2010; Ganser and Hewett, 2017). And lastly, the most advanced computational model variant is CFD models that have been applied in the workplace (Kassomenos *et al.*, 2008; Feigley *et al.*, 2011; MacCalman *et al.*, 2016; Dong *et al.*, 2017; Bennett *et al.*, 2018) and can predict both the continuous spatial and temporal dispersion of indoor aerosol concentrations in 2D or 3D. A 'disadvantage' of all these models is that the emission rate of sources must be known and the ventilation conditions should be relatively stable, and therefore the practicality and feasibility of applying these models in complex and dynamic workplaces (with variable conditions) are expected to be problematic.

Interpolation and concentration mapping

An interesting opportunity to pursue with time-resolved (miniature) sensor networks is the development of 2D and 3D concentration maps in the workplace. Spatial and temporal dispersion of airborne substances can be projected on 2D (or 3D) maps using interpolation techniques such as Kriging (Fig. 2; Peters *et al.*, 2006). Kriging is a geostatistical gridding method that interpolate concentrations measured at different sampling locations to create uniformly gridded spatial concentration maps. While mapping techniques do not require personal sensor data, a downside is that they may require rather extensive (high density) stationary sensor networks for accurate estimates (Peters *et al.*, 2006). Using Kriging, our research team has been able to combine both personal and stationary sensor data to develop concentration maps over longer time intervals (for example an hour). An alternative and more advanced option include Echo State Maps (Schaffernicht *et al.*, 2017), a methodology based on echo state networks that are well-suited for time-series analysis, non-linear signal processing, and spatial interpolation. This method combines a wireless sensor network with localized (mobile) robot measurements in order to create a dense interpolation model. It is also possible to expand these techniques with spatial–temporal interpolation models using Bayesian methods (e.g. Koehler and Volckens, 2011).

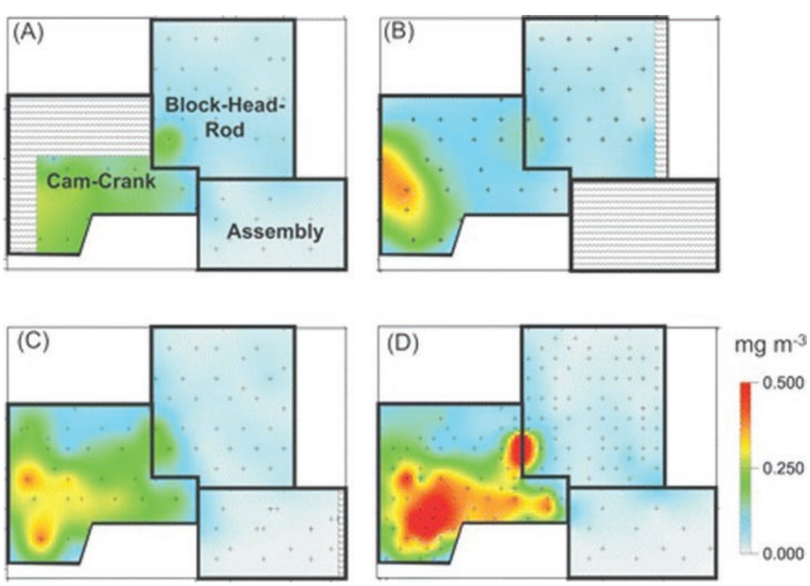

Figure 2. Example of respirable mass concentration 2D maps produced (using mapping software and Kriging) for an engine machining and assembly facility in the winter for different grids of sensor networks: (a) coarse-grid 1, (b) coarse-grid 2, (c) coarse-grid 3, and (d) fine (with permission from Peters *et al.*, 2006).

Interpolation techniques applied for concentration maps could be useful for the purpose of demarcation and zoning (segregation) of hazardous work areas, or to indicate the maximum period of time that a worker can spend in a given work area before the OEL is exceeded. Walking routes of employees at different locations can be determined to avoid hotspot areas, which are important for both compliance testing purposes and exposure control strategies.

Assimilation techniques

For more advanced source finding techniques and to detect and predict the variability of peak concentrations emitted from them (e.g. early warning systems), CFD can be used to fuse (or assimilate) model predictions and time-resolved sensor data. For this purpose, existing filtering systems (e.g. Kalman filters, Bayesian methods) used in environmental dispersion models can be used to improve the comparison between the concentrations predicted by the model and the measured concentrations (Curier *et al.*, 2012) by adapting the model parameters. These assimilation techniques can be applied to (re-)construct new data points within the range of known sensor data points and model estimates. Depending on the complexity of such models, their accuracy will be influenced by (for example) the number of point sources, the surrounding physical structures, and movement of workers at a work location. Similar to environmental dispersion models, the accuracy of these models can further be fine-tuned by optimizing the distribution of sensor networks and by improved parameterization of the model and model inputs (to cope with more dynamic environments). For example, research has shown that probability-based inverse CFD modelling could be applied in the design of more optimal sensor networks (Liu and Zhai, 2008).

Critical development and investment needs

It is clear that occupational exposure assessment professionals can greatly benefit from sensor technologies and their application in existing and new exposure models. It is widely accepted that by increasing the quantity of data the quality of the data can be improved (Hoover and Debord, 2015). Sensor data in itself is data-rich and can ultimately provide much more data, although it may only provide meaningful insights in exposure variability when it is synchronized with contextual information. However, limited field studies with sensors are available due to the fact that they do not yet have the specificity, selectivity, accuracy, and acceptable detection limits for reliable detection of specific substances in complex exposure scenarios in the workplace (AIHA, 2016; Sousan *et al.*, 2016). Miniature sensors are currently only sensitive (enough) to measure substance groups such as total volatile organic compounds and particulate matter (AIHA, 2016). Also, they require regular calibration and we can only benefit from their time-resolved functionalities if we also invest in (often costly) sensor information technologies that allow for wireless time-resolved data transport, data analysis, and storage. Despite these investments, sensors could become 'low cost' if one considers the wealth of information that can be obtained in terms of both data quantity and quality. With rapid innovations of the day, we expect that the use of miniature sensors will gradually become common practice in the workplace over the coming years.

To address long-term drift of sensors, the uncertainties of inherent use should be evaluated to establish the need for more 'in-the-field' validation for low-cost sensors. Research efforts should be invested to quantify and resolve these issues. In addition, calibration and validation protocols are needed to be able to interpret the validity and accuracy of sensor data obtained in field studies. It is evident that much more effort should be invested in model developments such as sensor-driven empirical models, interpolation, CFD, and assimilation techniques like Kriging. For example, further research is required to improve interpolation techniques and the development of concentration maps, as the complexity of workplaces and the resulting spatial–temporal variability and uncertainty could be a limiting factor in their development (Koehler and Volckens, 2011; Koehler and Peters, 2013). At the same time, measurement strategies and protocols must be adapted to align them with sensor data collection. Beside wearable sensors, the most optimal (stationary) sensor network distributions (incl. sample size) that are representative of a given workplace, should be investigated.

We are facing major challenges to facilitate the use of miniature sensors in the workplace. For new models to be developed, considerable effort is required in synchronizing time-resolved data with contextual information (e.g. location tracking; human activity tracking and recognition) in order to identify relevant exposure determinants of interest. Development of infrastructures, including data platforms and relevant architecture are required to integrate and channel the high volume and time series data from different sources. Methods should be developed to streamline these data streams to support data assimilation and data management. Also, privacy and security of sensor data linked to individual workers should receive adequate attention to ensure the privacy of individual workers and companies, focussing on the security of data (storage, analysis, sharing) and ethical issues of concern.

From a policy and regulation perspective, the use of sensor data may require new methods for compliance testing and sensor-specific exposure limits that are more in line with time-resolved exposures, its uncertainty, and its interpretation.

Conclusion

This commentary explored the possibilities of modelling with miniature sensor data, looking at enriching existing models and developing new ones. To develop sensor networks and new models, we identified a few important requirements: (i) to obtain more sensor data with reliable sensor technologies including the required methodologies, (ii) to invest in statistical and new model developments including data infrastructures, (iii) to comply with privacy and security issues and concerns, and (iv) to support different target groups to facilitate acceptance of these new technologies (workforces, employers) and for policymakers and technology developers to stimulate it. To this end, a collaboration and engagement in partnerships will be important to bridge the gap between researchers, industry, and policymakers, which will require a new way of thinking about high resolution and individualized data and how workplace exposures can be managed more effectively.

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Conflict of interest

The authors declare no conflict of interest.

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