School of Population Health

Expert elicitation, professional judgement, and current exposure assessment practices in the field of occupational hygiene

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This thesis is presented for the Degree of

Doctor of Philosophy

of

Curtin University

February 2023

Declaration

To the best of my knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Human Ethics: The research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research (2007) – updated March 2014. The proposed research studies received human research ethics approval from the Curtin University Human Research Ethics Committee (EC00262) - HREC approval number: HRE2021-0156

Signed: David Lowry

Date: 03 February 2023

Acknowledgements

My path in undertaking a PhD has been in equal measure incredibly challenging and extensively rewarding. Aside from the technical learnings, I feel I have developed resilience, tenacity, and most importantly, grown in my knowledge of myself and what I am capable of.

To my wife Kelley, you have always supported me in everything I do, thank you for your continued love, belief, and encouragement. To my children Hudson and Scarlett, the world is yours – believe in yourself and you can achieve anything you set your minds to.

My sincere thanks to my two supervisors, John Curtin Distinguished Professor Lin Fritschi and Professor Ben Mullins. Your guidance and expertise has been appreciated throughout the process, and I consider myself very fortunate to have been able to work with you both throughout the years. To Dr Rebecca O'Leary, thank you for the hours of work you dedicated to the statistical analysis in Chapters 5 and 6. The one-on-one guidance you gave me, as well as the follow up phone calls and emails, really assisted my learning in this area.

To John Curtin Distinguished Professor Lin Fritschi, thank you for seeing enough in me back in 2013 to support me through this journey. I am so grateful for the countless emails, phone calls, and face to face meetings, offering your valuable support, feedback and expertise. Thank you for sticking with me.

Finally, to my fellow occupational hygienists – thank you for everything you do.

Abstract

'Occupational Hygiene' is broadly described as the discipline of anticipating, recognising, evaluating and controlling health hazards in the working environment with the objective of protecting worker health and well-being and safeguarding the community at large. Occupational hygienists work across a diverse range of industrial environments. In the course of their work, hygienists will need to assess and control worker exposure levels by deploying methods based on the science of risk management, exposure assessment and industrial safety. Hygienists will regularly make decisions relating to worker exposure based on professional judgement, usually in the absence of quantitative data and in the presence of high uncertainty. These factors have the potential to lead to heterogeneity between practitioners, bias, error, and practice variation in the form of departure from established guidelines or protocols.

The primary aim of this PhD research project was to examine experience and current practices with respect to exposure assessment processes and judgement amongst occupational hygienists.

Study 1 (Chapter 3) investigated professional judgement, decision making, and current exposure assessment approaches of occupational hygienists via an online survey that was completed by 189 occupational hygienists worldwide. The results of this study suggest that practice variation in exposure assessment exists amongst occupational hygienists, with the primary findings being that hygienists use different strategies, and that deviations are largely driven by practical considerations like budget and site inspection findings. The responding hygienists identified opportunities to improve exposure assessment in the areas of randomised sampling, basic hazard identification, and task-based exposure monitoring.

Study 2 (Chapter 4) compared two methods of exposure assessment to ascertain the utility of task-based over full-shift monitoring. Full shift occupational noise measurements (n = 224) for a group of workers were taken and then compared to task-based noise measurements using linear regression analysis. Strong, positive, linear associations were found between full shift and task-based measurements (R^2

values above 0.85 for all job roles). Task-based exposure assessment has the potential to be used by occupational hygienists, particularly when tasks are well-defined.

Study 3 (Chapter 5) assessed professional judgment accuracy amongst occupational hygienists for a range of air contaminants (inhalable dust, respirable dust, crystalline silica) across four job roles in a mining environment using expert elicitation. An elicitation protocol was developed, and four occupational hygienists provided their subjective judgements for the air contaminants and job roles. These judgements were then compared to equivalent measured data using a scaled Beta distribution model. An overestimation bias was present for all participating occupational hygienists, and accuracy was higher when estimating percent of an exposure standard than the contaminant concentration.

Study 4 (Chapter 6) assessed professional judgment accuracy amongst occupational hygienists when subjectively assessing exposures to occupational noise across four job roles in a mining environment using expert elicitation. A similar method to *Study 3* was used. Findings suggest that overestimation of exposure values can occur when hygienists are completing subjective exposure assessments using decibel dose. In addition, hygienists may underestimate exposures when completing subjective assessments using percent of occupational exposure limit. The logarithmic scale used to measure decibels seemed to impact negatively on judgement accuracy for the participating hygienists.

This work in this thesis acts as a first step toward an introspective view of the occupational hygiene profession, as well as demonstrating the utility of three modalities of enquiry not commonly utilised within the field of occupational hygiene – survey, expert elicitation, and modelling – which can be used to further augment the current view of practice amongst occupational hygienists. The results of the studies within this PhD thesis present several opportunities for the occupational hygiene profession. First, heterogeneity exists between occupational hygienists and exposure assessment may be improved through the assimilation of real time monitoring, task-based assessment, and improvement in basic hazard characterisation into exposure assessment guidance. Further, task-based estimates of noise exposure can be useful in forecasting full-shift noise exposure, when calculated using specific tasks undertaken by job role. This indicates that task-based monitoring may be a suitable proxy for full-shift monitoring for those occupational hygienists who may be time and resource poor. Finally, subjective judgement accuracy amongst occupational hygienists is variable and different biases are present when completing subjective exposure assessments. Given the heavy reliance on subjective judgement in the profession, efforts should be made to improve the accuracy of the processes used by hygienists.

List of publications

The following papers were produced as part of the thesis. The papers were published in peer-reviewed international journals.

Paper 1: Occupational noise exposure of utility workers using task based and full shift measurement comparisons (Chapter 4)

Lowry, D., Fritschi, L., & Mullins, B. (2022). Occupational noise exposure of utility workers using task based and full shift measurement comparisons. *Heliyon*, e09747.

Paper 2a: Use of expert elicitation in the field of occupational hygiene: comparison of expert and observed data distributions (Chapter 5)

Lowry, D. M., Fritschi, L., Mullins, B. J., & O'Leary, R. A. (2022). Use of expert elicitation in the field of occupational hygiene: Comparison of expert and observed data distributions. *PloS one*, *17*(6), e0269704.

Paper 2b: Assessment of professional judgement in the field of occupational hygiene: comparison of expert and observed data distributions (Chapter 5)

Lowry D.M., Fritschi L., Mullins B.J., O'Leary R.A. (2022). Assessment of professional judgement in the field of occupational hygiene: comparison of expert and observed data distributions. *Safety and Health at Work*. 2022 Jan, Volume 13, Supplement, Pages S137-S138, ISSN 2093-7911, https://doi.org/10.1016/j.shaw.2021.12.1181.

Paper 3: Assessing accuracy of occupational noise exposure estimation using expert elicitation (Chapter 6)

Lowry D.M., Fritschi L., Mullins B.J., O'Leary R.A. (2022). Assessing accuracy of occupational noise exposure estimation using expert elicitation. *Manuscript submitted for publication.*

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Abbreviations

ACGIH	American Conference of Governmental Industrial Hygienists
AIHA	American Industrial Hygiene Association
AIOH	Australian Institute of Occupational Hygienists
BDA	Bayesian Decision Analysis
BOHS	British Occupational Hygiene Society
ESG	Environmental, Social and Governance
GSD	Geometric Standard Deviation
HPD	Hearing Protection Device
HSE	Health and Safety Executive
ILO	International Labour Organization
IOHA	International Occupational Hygiene Association
MVUE	Minimum Variance Unbiased Estimator
NIHL	Noise Induced Hearing Loss
NIOSH	National Institute for Occupational Safety & Health
NVvA	Nederlandse Vereiniging voor Arbeidshygiene
OECD	Organisation for Economic Co-operation and Development
OEL	Occupational Exposure Limit
OESSM	Occupational Exposure Sampling Strategies Manual
OSHA	Occupational Safety and Health Administration
PPE	Personal Protective Equipment
SEG	Similar Exposure Group
SPL	Sound Pressure Level
TWA	Time Weighted Average

UCL	Upper Confidence Limit
WHO	World Health Organization

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Chapter 1: Introduction

“To the questions recommended by Hippocrates, he should ask one more – what is your occupation?”

This statement has been credited to Bernardino Ramazzini, the Italian physician and celebrated ‘Father of Occupational Medicine’ and was considered at the time to be an appeal to fellow physicians to draw a link between adverse health outcomes and working conditions (1).

Lead poisoning, the discovery of which has been attributed to Hippocrates around 370 B.C., is widely accepted to be the oldest recognised occupational disease (2). In what may be described as a very early application of exposure assessment and professional judgement, the Greek physician attributed a severe case of colic in a worker who extracted metals to lead poisoning (2). Hippocrates’s astute link between the work environment and disease could be thought of as the first appearance of the field of occupational hygiene, which can be defined as the anticipation, recognition, evaluation and control of health hazards in the working environment with the objective of protecting worker health and well-being and safeguarding the community at large (3).

The relationship between conditions of the work environment and worker health outcomes has long been established and was originally championed within the field of occupational medicine (1). The first recognition of the occupational hygiene profession was preceded by at least 200 years of developments in disease prevention practices in the workplace, many of which could be characterised as occupational hygiene (4). In many countries, the nature and pace of adoption of these practices depended on the current state of technology, science, medicine and social concern. The first occupational hygiene practitioners did not depend on quantitative data; however, by the second half of the 19th century, techniques of measurement for both harmful effects and for exposure were being introduced and official bodies for occupational hygienists at both national and local levels were active. By 1920 most of the major concepts and practices of current occupational hygiene practice were in place (4).

From a contemporary standpoint, measurement techniques have advanced; however, the need for an occupational hygienist to deploy subjective reasoning based on experience and intuition to come to a decision about the impact of the work environment – what we would term *professional judgement* - remains a cornerstone of the profession.

This chapter presents the background and the rationale for conducting this PhD research project, states the aims, and provides an overview of the chapters of the thesis.

1.1 The case for Occupational Hygiene

"It's shocking to see so many people literally being killed by their jobs"

These words are attributed to Dr Tedros Adhanom Ghebreyesus, World Health Organization (WHO) Director-General, who in 2021 delivered the sobering news that work-related diseases and injuries were responsible for the deaths of 1.9 million people worldwide in 2016. This statistic was part of a wider study, the first joint estimate report from the WHO and International Labour Organization (ILO) entitled *WHO/ILO Joint Estimates of the Work-related Burden of Disease and Injury, 2000-2016: Global Monitoring Report* (5). The study considered 19 occupational risk factors, including workplace exposure to air pollution, asthmagens, carcinogens, ergonomic risk factors, and noise. The majority of work-related deaths were due to respiratory and cardiovascular disease, with 450,000 deaths attributable to workplace exposure to air pollution (particulate matter, gases, fumes); however, the report noted that total work-related burden of disease is likely to be substantially larger (5).

In addition to reporting hard numbers and statistics, the joint estimate report articulated a unique set of preventive actions and controls for each risk factor to guide governments, in consultation with employers and workers. For example, the prevention of exposure to workplace air pollution requires dust control, ventilation, and personal protective equipment (PPE) to be prioritised (5). To reduce workplace exposure to noise, interventions that introduce engineering controls (e.g., reducing noise emission from industrial machinery), impose administrative controls (e.g. limiting the time a worker spends in noisy environments), monitor noise, carry out audiometric testing, train workers, and enforce the wearing of PPE are required (5). In total, the word 'exposure' is mentioned 396 times in a 92-page report.

The term *exposure* can be defined as 'the contact between an agent (e.g., a pollutant) and a target (e.g., a person's hand)' (6). Determining the risk to humans posed by a potential hazard can be viewed in the following sequence,

a) contaminant source(s),

b) concentration,

c) human exposure (i.e., contact),

d) dose (i.e., the amount of contaminant that enters the human), and

e) resulting health effects (7)

Each part of the sequence is dependent on the previous one – without human contact with a contaminant, there can be no corresponding exposure; without exposure, there can be no corresponding dose or risk. Therefore, understanding each component and the relationship between them can assist in determining effective health risk management strategies (6, 8). A key benefit of assessing exposure as opposed to dose is that it allows for the anticipatory, as opposed to reactive, management of health hazards before they manifest as health impacts to the workforce.

The need for a profession to diagnose 'exposure' as opposed to 'disease' opened the door for the occupational hygiene profession to introduce its own unique process of assessing and managing health exposure problems. Occupational Hygiene is now understood to be the practice of identifying hazardous agents; chemical, physical and biological; in the workplace that could cause disease or discomfort, evaluating the extent of the risk due to exposure to these hazardous agents, and the control of those risks to prevent ill-health in the long or short term (3). The word 'hygiene' is derived from the name of the Greek goddess of health known as Hygeia, the daughter of Asklepios and sister of Panacea (9). Whilst Hygeia's father and sister were connected with the treatment of existing disease, Hygeia herself was regarded as being concerned with the preservation of good health and the prevention of disease (3).

Occupational hygienists are practitioners with broad multidisciplinary scientific training, traditionally grounded in the physical, life, and behavioural sciences (10). Their key mission of anticipation, recognition, evaluation and control of potential hazards in the working environment means that occupational hygienists are often seen as partners to occupational health physicians, toxicologists, environmental health practitioners, nurses, and safety professionals. This multidisciplinary team approach concept has become a central philosophy in the study and practice of modern occupational health (11). Ronald E. Lane, the first professor of occupational medicine at a British university, noted in his 1978 memoir that *"the establishment of occupational hygiene was, in my view, a logical and essential development. Without the hygienists' accurate measuring techniques, the doctor in industry has a very restricted value. It is important to realise, however, that our spheres of action are complementary; the hygienist cannot replace the doctor any more than the doctor can work effectively without the hygienist"* (12).

Work-related diseases and injuries strain health systems, reduce productivity, and can have a catastrophic impact on household incomes (5, 13, 14). The prevention of such disease burdens is a core goal of the discipline of occupational hygiene.

1.2 Background

Occupational hygienists are frequently relied upon to provide accurate exposure judgements. These judgements are used to quantify the magnitude of a health hazard in the work environment in order to inform and suggest an appropriate level of *control*, the definition of which is the steps that can be taken to reduce the risk associated with the hazard (15). The hierarchy of controls has five levels of actions to reduce or remove hazards, with the preferred order of action based on general effectiveness being elimination, substitution, engineering controls, administrative controls, and personal protective equipment (16). Using this hierarchy can lower worker exposures and reduce risk of illness or injury. To do this, the occupational hygienist has access to standardised exposure assessment strategies, guidelines, and tools, the majority of which were developed many years ago and are still currently in place. Currently, we do not have an overview of which strategies and tools are most used by practicing occupational hygienists, or whether these practitioners agree with the utility of these exposure assessment strategies given their own experiences.

Most exposure assessment strategies require the workforce to be categorised into similar exposure groups (SEGs) (17-19). Most commonly, occupational hygienists use a combination of personal experience with a given type of operation, review of exposures from similar operations, similar tasks or chemicals, and exposure predictions developed using physical and/or chemical exposure modelling techniques to assign an initial exposure rating and prioritise their SEGs for further actions. Based on this prioritisation, a baseline monitoring campaign is carried out for some SEGs and the measurement data collected are used to refine the initial rating and determine if the exposure distribution is acceptable. Acceptability is commonly evaluated by comparing an upper percentile, such as the true group 95th percentile to the occupational exposure limit (OEL) (20). In the American Industrial Hygiene Association (AIHA) strategy, the 95th percentile of the exposure distribution is estimated along with its upper confidence limit (UCL) (21). Based on the magnitude of the group 95th percentile and its UCL relative to the OEL, the exposure is classified into one of four categories: Category 1 or ‘highly controlled’, Category 2 or ‘well controlled’, Category 3 or ‘controlled’, and Category 4 or ‘poorly controlled’ (18, 19, 21). This classification becomes the basis for decisions regarding exposure management (21-24).

However, what of those occupational hygienists who may be time and resource poor? Is an elaborate exposure assessment strategy a realistic undertaking for a consultant who has been brought in to assess and manage a potential health risk with finite resourcing, and time and budget constraints? For instance, the aforementioned AIHA strategy calls for collecting 6–10 measurements for most SEGs that are to be evaluated using exposure monitoring (18, 19, 21). Obtaining such data can be expensive and time consuming, and in many workplace settings, the demand for more accurate and precise results is at odds with limited resources (25). Practically, due to resource constraints, most exposure assessments are made with either fewer than six monitoring data points or no data at all (24). Often, in the absence of sufficient data, occupational hygienists interpret the available workplace information using their professional judgment and make decisions regarding appropriate controls. Therefore, there is a heavy reliance on the accuracy of professional judgments and the ability of occupational hygienists to correctly integrate them with monitoring data to make accurate exposure decisions. Professional judgment is the ability of an experienced professional to make correct inferences using incomplete data (19).

It must also be considered how current exposure assessment strategies and tools align with the future of work. Many industries are choosing to optimise the productivity of their workforce through the addition of highly dynamic, generalist job roles as opposed to specialised trades and skillsets (26, 27). Consider the example of the mining industry, where workers nowadays are expected to maintain and operate a wide range of mobile and fixed equipment and tooling, which suggests a move from the higher specificity job roles of the past to a 'jack of all trades' (28). From a personal exposure standpoint, the move from job roles with expected or predictable health hazards, to one in which the work environment becomes more dynamic and less predictable, presents a significant challenge to the occupational hygienist, particularly given the standardised models of 'full-shift' sampling established many years ago (29). A primary issue is that, if after sampling, the occupational hygienist receives a result for a worker in a dynamic job role that is above the workplace exposure standard, it is a significant challenge for the hygienist to identify the *source* of the primary exposure to suggest adequate control options. Simply asking the worker what they did over the course of the sampling day is standard practice to identify high exposure areas and tasks; however, it is known that the validity of self-report data declines with the precision required by the data (30-32). Therefore, the sampling result becomes less useful if the goal is to target and control exposure sources in a risk-based way.

Another major influence is the shift of employment demographics that has taken place in high income countries in the recent years (33). There has been a decrease in the proportion of the total workforce engaged in large industrial concerns and a corresponding increase in the proportion working in small and medium-sized enterprises (34, 35). In the first instance this has led to changes in basic occupational hygiene practice, with smaller cohorts exposed to different agents under different working conditions. In turn, there is now reduced employment of occupational hygienists in industrial corporations and an increase in the outsourcing of occupational hygiene services to consultancy companies (34). Overall, there has been a decline in employment in primary production and manufacturing industries in the high income countries, matched by increases in the low or middle income countries as corporations have migrated to seek cheaper labour markets (36). It is evident that, whilst the needs for occupational hygiene have shifted in the developed world, the traditional demands are greater than ever elsewhere (36).

It should be noted also that the practice of occupational hygiene has spread far beyond traditional industrial settings to include non-industrial workers (office workers, health care workers, etc.) (34, 37). In parallel, occupational hygienists are becoming increasingly involved in the wider field of environmental hygiene, including hazardous materials (29), emissions to the general environment (38), safety and security (39), and psychosocial health (40-42) which requires knowledge not only about a wider range of scientific issues but also of a much more diverse regulatory framework (34). In some jurisdictions, the role of the occupational hygienist is becoming less ‘hands-on’ as the measuring and monitoring of workplace conditions is replaced increasingly by the administration of programs and management systems (34). Therefore, the occupational hygienist's role is moving closer to that of a ‘risk manager’.

In addition, digitalisation and globalisation are causing significant changes in the way our societies live and work (27, 43). Artificial intelligence and automation will make this shift as significant as the introduction of mechanisation in prior generations of agriculture and manufacturing (44). The coronavirus (COVID-19) pandemic has accelerated these changes and added an extra dimension to the problem of how we adapt in an ever-changing work environment, with organisations revaluating many aspects of their work (45-47). These changes raise essential questions around the nature of work, the skills needed for current and future jobs, and how best functional services – such as those offered within the wider field of occupational health - will support these jobs (48, 49). Nearly 14% of jobs in the Organisation for Economic Co-operation and Development (OECD) member countries are likely to be automated, while another 32% are at high risk of being automated (36). Technology and internet access has allowed many workers to continue their jobs at home during the pandemic; however, not everyone has had that option (50). Jobs that require physical access are now more likely to be held by lower-skilled workers and those in retail, manufacturing and transport sectors. While some jobs will be lost, and many others created, it is anticipated that almost all will change (36, 49).

This raises some important challenges for the profession of occupational hygiene. Considering all of the impending changes described, how will current strategies, practices, and tools utilised by practicing hygienists remain useful and relevant, and how will hygienists adapt more generally in light of these changes? Currently, hygienists entering the field are largely being trained to assess and control exposures using approaches developed under old models of work and risks which may not adequately address health hazards in the workplace of the present and future (51, 52).

The decision processes employed by individual hygienists when doing qualitative, quantitative, or semiquantitative assessments to estimate occupational exposure remain relatively unknown (53). It is often assumed that, because of uniform training and guidelines, there is one common method by which all hygienists complete their assessment which can be captured in a globally applicable conceptual model (24, 53, 54). However, it is more likely that conceptual models will differ between individual experts because of their training, experience, familiarity with the process, and other factors (53). As a result, in situations where subjective judgements cannot be directly compared to exposure measurement data, it is difficult to assess the quality and validity of these judgements or even to compare the judgements of different experts with each other.

1.3 Significance

There are several key reasons as to why this research was undertaken. First, the nature of work is rapidly changing, with a shift to more dynamic job roles, increased automation, and a larger step toward distributed work options (i.e., flexible work arrangements) for employees (36, 48). These changes present three challenges to the practice of occupational hygiene, which can be described as follows,

1) the requirement to anticipate and recognize newer hazards that may be present in the work environment commensurate with changes in working conditions as described above (i.e., technological changes such as automation, artificial intelligence)
2) the acknowledgement that, although these newer hazards may be presenting more frequently in high income countries, traditional hazards (physical, chemical, biological) will still need to be addressed and controlled in low or middle income countries, and
3) the need for occupational hygienists to refine their practices and standardised tools (many of which were devised many years ago) in order to remain agile and stay relevant in light of these changes (19)

The traditional ways in which an occupational hygienist approaches their work, particularly in the areas of measuring and monitoring, are also changing (52). There has been a decline in occupational hygienists employed by industrial corporations and an increase in the outsourcing of occupational hygiene expertise to consultancy companies (34, 55). There has been a rise in the tendency to out-source occupational hygiene-related activity to remove what had increasingly been seen as an overhead, and with this has come a corresponding rise in occupational hygiene consultancy (34, 55).

In this scenario, the occupational hygienist needs to be a generalist since they can no longer expect to spend their entire career in one industry dealing with a single set of occupational hygiene problems that, although they evolve, remain constrained. The practical implication of this has meant a reduction in baseline-type sampling programs, which use randomisation and full-shift sampling methods to describe a worker's exposure to a hazardous agent, and an increase in shorter sampling campaigns that yield fewer data points on which to make exposure decisions, usually in the presence of high uncertainty (56). This puts a higher onus on the importance of accurate professional judgements to fill in any gaps in quantitative data in order to adequately protect the worker. However, judgement accuracy is often linked to experience, education and training (53), and so the challenge becomes how to ensure practicing hygienists are best able to navigate the issues associated with exposure assessment decision making in the absence of measured data. This extends to the level of comfort a hygienist would have in making an exposure decision under these conditions, and then communicating this decision to senior management stakeholders.

In addition, for many businesses worldwide, regulatory pressure and Environment, Social and Governance (ESG) strategies are encouraging the corporate sector to act responsibly beyond seeking profits, with a strong focus on partnership, corporate citizenship, and 'being a good neighbour' within the communities in which they are situated (45, 57). Healthy workplaces are essential for global development and progress, and occupational hygienists, with their expertise in anticipating, recognising, evaluating and controlling workplace hazards, will play an important part in this effort (45, 57). Given this, there is an essential need for robust practices, accurate decision making, and credibility in order that the profession continues to be relevant and useful.

This research seeks to understand current experience and practices with respect to professional practice and judgement amongst occupational hygienists by: surveying occupational hygienists to gain an understanding of current process, decision making, and any variation from standard work practices; comparing two methods of exposure assessment to ascertain the utility of task-based over full-shift monitoring; and assessing professional judgement accuracy amongst occupational hygienists. It is hoped that the outcomes of this research can help inform future training and education programs for practicing occupational hygienists to help them better navigate the challenges described.

1.4 Aims and outline of the thesis

The impetus for this research has centred around three key research questions:

1. How do occupational hygienists describe their experience and current practices with respect to exposure assessment practice and judgement?

2. For occupational hygienists who cannot follow a standardised approach for exposure assessment due to varying constraints, what other avenues are available?

3. Accuracy in exposure assessment is important. Sometimes occupational hygienists need to make decisions based on very little (or no) measured data – how good are they at doing this?

In total, this thesis comprises of seven chapters (including this introductory chapter), which are summarised below:

Chapter 2: Literature review - is an overview of the discipline of occupational hygiene and the key practice areas relating to exposure assessment, expert elicitation, decision making, and professional judgement. A statement of current research gaps is also given.

Chapter 3: Description of experience and current practices with respect to professional practice and judgement – presents the results of a survey undertaken by occupational hygienists focusing on current practices, with a specific focus on exposure assessment and decision-making.

Chapter 4: Occupational noise exposure of utility workers using task based and full shift measurement comparisons (published paper) – presents an exposure assessment comparison study whereby task-based measures of exposure are compared to full shift measures of exposure to understand whether this is a useful tool for the practicing hygienist.

Chapter 5: Use of expert elicitation in the field of occupational hygiene: comparison of expert and observed data distributions (published paper) – presents a study conducted to assess the professional judgement accuracy of occupational hygienists using an elicitation protocol to capture subjective air contaminant estimates, which was then compared to the equivalent measured exposure data.

Chapter 6: Assessing accuracy of occupational noise exposure estimation using expert elicitation (manuscript under review) – in the final study of this thesis, the same methodology outlined in Chapter 5 is applied to assess accuracy in professional judgement for occupational noise estimates in a group of hygienists. These estimates were then compared to the equivalent measured exposure data.

Chapter 7: General discussion and conclusion - provides the conclusion of the thesis and offers a general discussion on the results and relevance of the findings and describes the limitations and implications for future research, education and professional practice opportunities, and policy.

Chapter 2: Literature review

2.1 A brief history of occupational hygiene

The genesis of what would become to be known as occupational hygiene practice has its roots in antiquity, and much of the early work in terms of understanding and managing the risk of work-related exposure was done by physicians. The occupational environment and its relationship to worker health was recognised as early as the fourth century B.C. when the Greek physician Hippocrates noted lead toxicity in the mining industry (2). In the first century A.D., a Roman scholar named Pliny the Elder identified health risks to those working with zinc and sulphur, to the extent that he devised an early form of a face mask made from an animal bladder to protect workers from exposure to dust and lead fumes (58). In the second century A.D., the Greek physician Galen accurately described the pathology of lead poisoning and recognised the hazardous exposures of copper miners to acid mists. In the Middle Ages, various guilds - medieval associations of craftsmen or merchants - worked at assisting sick workers and their families (59).

In 1556, the German scholar Agricola advanced the science of industrial hygiene even further when, in his book *De Re Metallica (On the Nature of Metals)*, he described the diseases of miners and prescribed preventive measures (60). The book included suggestions for mine ventilation and worker protection, discussed mining accidents, and described diseases associated with mining occupations such as silicosis. Around the same time, the Swiss physician Paracelsus was introducing concepts from chemistry into his medical practice, the basis of which would become the discipline of modern toxicology (61). In his 1538 book *Die dritte Defension wegen des Schreibens der neuen Rezepte (The Third Defense in Writing New Prescriptions)*, Paracelsus coined a quote that is now well known within the practice of occupational hygiene, *“All things are poison, and nothing is without poison; but the dose makes it clear that a thing is not a poison”* (62). This quote has now been reduced to a more familiar shorthand, ‘The dose makes the poison’ (63). Paracelsus was also the first physician to write a book on occupational disease in 1567 which was titled *Von der Bergsucht und anderen Bergkrankheiten (On the miners' sickness* *and other miners' diseases)* which described mining-related respiratory diseases, like pulmonary tuberculosis and lung cancer (64).

The roots of occupational hygiene progressed further in 1700 when Bernardo Ramazzini – the 'father of occupational medicine' - published in Italy the first comprehensive book on industrial medicine, *De Morbis Artificum Diatriba (The Diseases of Workmen)* (65). The book contained accurate descriptions of the occupational diseases of most of the workers of his time. Ramazzini greatly affected the future of occupational hygiene because he asserted that occupational diseases should be studied in the work environment rather than in hospital wards. The progression of occupational hygiene received another major boost in 1743 when the Austrian physician Ulrich Ellenborg published a pamphlet on occupational diseases and injuries among gold miners. Ellenborg also wrote about the toxicity of carbon monoxide, mercury, lead, and nitric acid (66).

In England in the 18th century, the physician Percival Pott, as a result of his findings on the development of scrotal cancer amongst chimney sweepers on account of excessive 'soot' exposure, was a major force in getting the British Parliament to pass the Chimney-Sweepers Act of 1788 (67). The passage of the English Factory Acts beginning in 1833 marked the first effective legislative acts in the field of industrial safety. The Acts, however, were intended to provide compensation for accidents rather than to control their causes. Later, various other European nations developed workers' compensation acts, which stimulated the adoption of increased factory safety precautions and the establishment of medical services within industrial plants (67).

In the early 20th century in the U.S., Dr. Alice Hamilton led efforts to advance the field of occupational hygiene. In 1919 Hamilton became the first woman to be appointed to the staff at Harvard Medical School, where she also conducted studies on industrial pollution for the federal government and the United Nations. Hamilton wrote several books including *Industrial Poisons in the United States* (1925), *Industrial Toxicology* (1934), and *Exploring the Dangerous Trades* (1943). Hamilton observed industrial conditions firsthand and raised the poor conditions with mine owners, factory managers, and state officials with evidence that there was a correlation between worker illness and exposure to toxicants. Hamilton also progressed the field of exposure control when she presented definitive proposals for eliminating unhealthful working conditions (68).

At about the same time, U.S. federal and state agencies began investigating health conditions in industry. In 1908, public awareness of occupationally related diseases stimulated the passage of compensation acts for certain civil employees (69). Certain U.S. states passed the first workers' compensation laws in 1911, and in 1913, the New York Department of Labor and the Ohio Department of Health established the first state occupational hygiene programs. All U.S. states enacted such legislation by 1948 (69).

In Australia, the Federal Government created the first Department of Health in 1921 in direct response to population outcomes sustained from the Spanish flu (70). The Department went on to complete some pioneering work in 1925 to prevent silicosis in miners in the Goldfields region of Western Australia through the use of a portable x-ray machine (70). From 1950 – 1960 tuberculosis was reduced with x-ray checks and vaccination around Australia (70).

In the late 1950s, a step change occurred in the history and advancement of occupational hygiene. Around this time, there were a few large organisations committed to monitoring dust and vapours in workplaces (71) in particular, the early practices of monitoring of dust in coal mines and gases and vapours in the oil industry were slowly beginning to take root. The instruments that were used for these purposes were portable; however, they were not sufficiently reliable or lightweight to allow for personal sampling. For aerosols, the instruments being used included the thermal precipitator (developed 1936–37), the Pneumoconiosis Research Unit hand pump (1948), the konimeter (1927), the Owens jet sampler (1923) and others (72). In England, a scientist from the UK Atomic Energy Authority, Jerry Sherwood, and his colleagues were interested in monitoring radioactive dust in the emerging UK nuclear power industry. A landmark event in the development of occupational hygiene practice occurred when Jerry Sherwood and his colleague Don Greenhalgh were the first to build a practical personal sampling pump. Their paper describing the invention, ‘A personal air sampler’, was published in 1960 in the second volume of the *Annals of Occupational Hygiene* (73). The development of the personal sampling pump by Sherwood and Greenhalgh heralded the beginning of modern occupational hygiene and provided the foundation for a proper scientific underpinning of professional practice. It led to a period of enthusiastic monitoring of personal exposure, which not only helped control exposures on a case-by-case basis but provided the knowledge base for subsequent developments (71).

Post-1950, the U.S. Congress passed three landmark pieces of legislation related to safeguarding workers' health: (1) the Metal and Non-metallic Mines Safety Act of 1966, (2) the Federal Coal Mine Safety and Health Act of 1969, and (3) the Occupational Safety and Health Act of 1970 (OSH Act) (69). The passing of this legislation ensured that employers in the U.S. were required to implement the elements of an industrial hygiene and safety, occupational health, or hazard communication program and to be responsive to the Occupational Safety and Health Administration (OSHA) and its regulations (69).

With the advent of governments in the U.S. and elsewhere passing legislation specifically aimed at protecting and preserving worker health, and the demand for increasing regulation of the quality of working environments and workers' exposures to harmful agents, the need for a group of professionals dedicated specifically to the field of occupational hygiene was realised (34). The profession eventually coalesced around five key areas:

1. Enabling employers to comply with standards set by governments
2. Dealing with specific hygiene-related technical and management problems
3. Providing new knowledge through research
4. Providing leadership in the organisation and maintenance of occupational hygiene programs in work settings; and
5. Providing leadership in policy and standards development (10, 34)

The development of the first occupational hygiene societies originated in the U.S., beginning with the first convening members for the American Conference of Governmental Industrial Hygienists (ACGIH) in 1938, and the formation of the American Industrial Hygiene Association (AIHA) in 1939 (34). In the United Kingdom, the British Occupational Hygiene Society (BOHS) started in 1953 (74), with the Australian Institute of Occupational Hygienists (AIOH) forming in 1980 (75). Through the years, professional occupational hygiene societies have formed in many countries, leading to the formation of the International Occupational Hygiene Association (IOHA) in 1987 to promote and develop occupational hygiene worldwide through the member organisations (34). The IOHA has grown to 29 member organisations, representing 20,000 occupational hygienists worldwide with representation from countries in every continent (76). The discipline of occupational hygiene now serves an important function across many industries worldwide.

Notwithstanding this, in recent years the practice of occupational hygiene has undergone significant change and development (77). The primary reasons for this include technological changes that have introduced new health hazards into the workplace (for instance, the advent of nanomaterials and their potential for deleterious effects on the body (78-80)); continued increases in health and safety legislation and regulations (81, 82); increased pressure from regulatory agencies (83); realisation by industrial executives that a safe and healthy workplace is typically more productive (84, 85); high health care and workers' compensation costs (5, 86); increased pressure from environmental groups and the public (87); a growing interest in ethics and corporate responsibility (87, 88); and professionalisation of the occupational hygiene discipline as a bonafide practice (77). On aggregate, these factors have made the role of the occupational hygienist more challenging and more important than it has ever been.

2.2 The concept of exposure assessment

The definition of occupational hygiene, centred around the tenets of anticipation, recognition, evaluation and control, speaks to the complexities and diversity within the profession. The practicing hygienist will be expected to do many things; however, the 'evaluation' component of a hygienist's role directly relates to the concept of exposure assessment (21).

To undertake an exposure assessment is to understand the nature and magnitude of a hazard posed by a particular agent on the population of interest (89). Exposure assessment is central to an occupational hygiene program as it provides the foundation for all of the functional elements underpinning these programs (see Figure 1) (19). A well-rationalised program relies on a thorough understanding of what is known (and not known) about exposures. For example, to understand where best to spend resources on a monitoring program, occupational hygienists must understand potential exposures that need better characterisation or routine tracking (19). A thorough characterisation of exposures allows the occupational hygienist to focus worker training programs, better target medical surveillance programs, and define specific requirements for PPE and higher order controls such as engineering and elimination (19, 29).

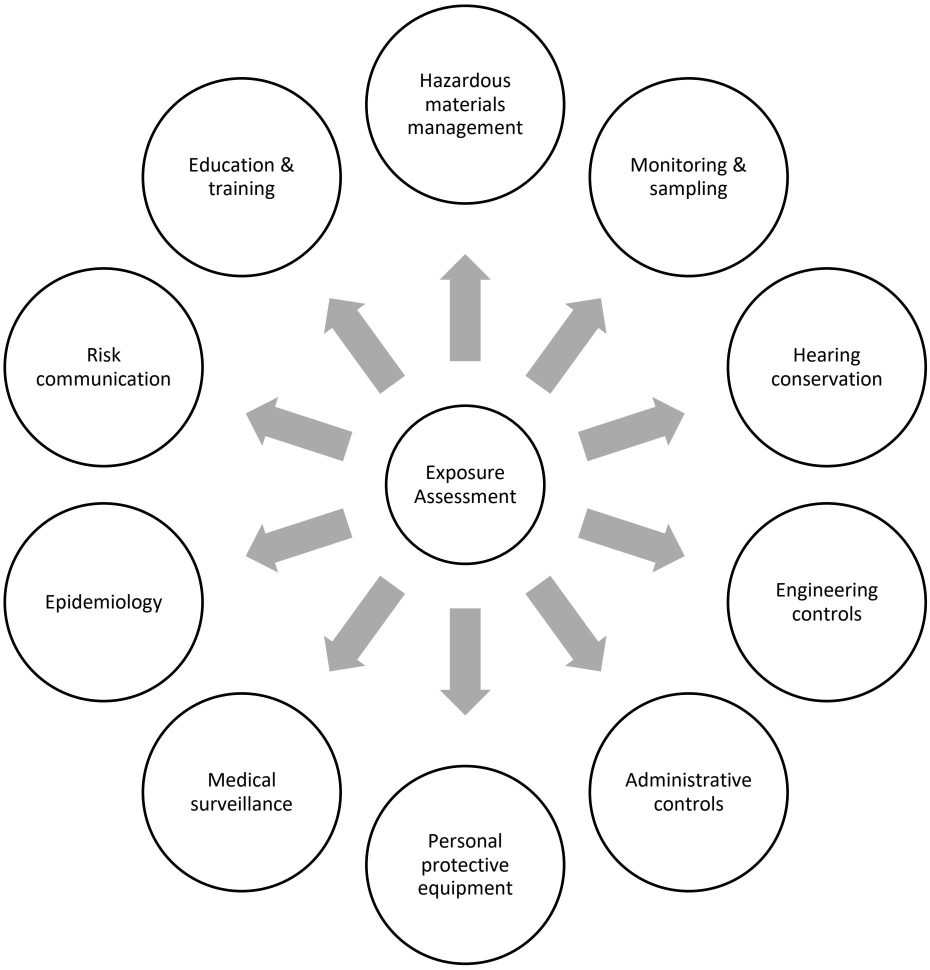

Figure 1 The central role of exposure assessment within the context of a broader occupational hygiene management program (adapted from Jahn, S. D., Bullock, W. H., & Ignacio, J. S. (Eds.). (2015)

An exposure assessment can be carried out for a variety of reasons, and the design of the assessment strategy should be dependent on the context (90). The most common reason is routine monitoring of worker exposures to chemical and physical hazards in the workplace and comparison of these exposures with an occupational exposure limit (21, 91). This can be done by occupational hygienists employed by a company for routine risk management or by regulatory enforcement agencies to determine whether exposure levels meet legal standards. Another important reason might be to determine a relationship between exposure and health outcome in an occupational epidemiology study (92-94).

The purpose of conducting an exposure assessment also drives the choice of the decision statistic in the analysis. For example, if the exposure assessment is done in the context of an epidemiological study, some measure of central tendency such as the arithmetic mean is appropriate (21, 91). In contrast, if exposure assessment is done for routine risk management, i.e., to ensure that most of the workers have acceptable exposure levels, then some upper percentile of the exposure distribution (e.g., the 95th percentile) may be a better decision statistic (23, 91, 93).

Exposure variability is one of the most important factors that should be considered while designing exposure assessment strategies (90, 95). Exposures vary between workers with the same job title but with differences in the tasks that comprise the job; even for workers doing the same task, exposures vary between workers and over time, shift and location (95). The sampling strategy should be capable of estimating this variability (96). In addition, the sampling strategy should be effective (i.e., provide correct exposure decisions) and efficient (i.e., use a minimum of resources). These requirements of effectiveness and efficiency are typically at odds with each other, and any exposure strategy needs to strike a balance between these competing needs (90, 91).

2.3 Exposure assessment strategies and practices

Occupational hygienists have access to a number of strategies and practices to assist in the goal of exposure assessment. Many of these strategies are focused on compliance, whereby a maximum-risk worker is assessed to determine whether exposures are above or below an established limit. However, more contemporary strategies have begun to focus on a more comprehensive exposure assessment, which emphasises characterisation of all exposures for all workers on all days (21, 97).

One of the most well-known exposure assessment strategy documents is the National Institute for Occupational Safety and Health (NIOSH) *Occupational Exposure Sampling Strategies Manual (OESSM)* (98). The manual, published in 1977, has been the basis of the U.S. Occupational Safety and Health Administration's (OSHA's) compliance enforcement strategy, and has been relied upon by many occupational hygienists worldwide as a primary tool on which to base exposure assessment activities. Nevertheless, it may be the case that the NIOSH manual is now less useful on account of fundamental changes within the practice of occupational hygiene in the decades since it was written (91).

The NIOSH manual describes a strategy to assess compliance on a single day for a single worker, e.g., a maximum risk employee (98). This is achieved typically by using one or at most two measurements. Compliance is tested by a measurement-by-measurement comparison with the relevant exposure standard, requiring no understanding of exposure variability or the statistical calculations needed to estimate it. Therefore, only sampling and analytical variability associated with each measurement is accounted for despite the fact that this is of much less consequence when compared to environmental variability (99). A research study reported that the strategy could not reliably detect poorly controlled exposures, calculating a power of only 50% to detect a clearly unacceptable exposure profile with a 25% exceedance fraction (100). Thus, whilst the NIOSH strategy is very efficient (requiring very few measurements), it is ineffective because it fails in the very task it sets out to accomplish, i.e., accurately identify work scenarios that are not in compliance. Rappaport (101) showed that compliance status depends very strongly on the number of measurements and that the strategy perversely provides a disincentive to increasing the number of measurements. The strategy is also limited in that substances with no exposure standard, dermal, and psychosocial hazards cannot be evaluated using this framework (91). In addition, the NIOSH strategy produces data that typically cannot be used for other purposes, e.g., risk management or epidemiology. For instance, by focusing sampling on ‘maximum risk employees’, the strategy will likely overestimate exposures and underestimate variability and be unrepresentative for epidemiological purposes.

In the United Kingdom, the Health and Safety Executive (HSE), a government agency responsible for the regulation and enforcement of workplace health, safety and welfare, and for research into occupational risks in Great Britain, has developed a strategy document entitled *Monitoring strategies for toxic substances* (102). Published in 2006, the strategy is similar to the NIOSH method; however, is considered more inclusive as it takes in more of the exposed workers than the NIOSH method’s approach of sampling a single worker. Compliance can be judged as having been achieved if three-quarters of 12 or more results on the most exposed workers are below one-third of the relevant OEL (102). This method relies on some assumptions, chiefly that the results are log-normally distributed, the most exposed workers are properly identified, and geometric standard deviations are not excessive (i.e. < 2.5) (102). The method is also based on the knowledge that, if three-quarters of results lie in the lower one-third of a distribution, then the percentage of the distribution above the OEL will most likely be lower than 5% (102). A limitation of this strategy is that, if the most exposed workers are not identified and measured, and the assumptions do not hold if there are less than 12 samples taken (for example due to cost or resourcing constraints).

A strategy proposed by the AIHA (18, 21, 97) was initially developed and published in 1991 and has since had three revisions (1998, 2006, and 2015). The strategy offers a comprehensive approach that combines observational and sampling tactics for defining SEGs and integrates more contemporary concepts in occupational hygiene assessment such as Bayesian statistics. The strategy also recommends a fifth element in the occupational hygiene decision-making framework in addition to anticipation, recognition, evaluation and control, this being the concept of ‘confirm’. The AIHA has stated that the addition of this extra element is a critical step in validating that exposure assessment and professional judgements are correct and that selected controls are reducing exposures to the desired level (21). This strategy appears to strike a balance between using the professional judgments of occupational hygienists to classify SEGs and obtaining sufficient measurements in situations that warrant it. The strategy does make some key suppositions in that it assumes qualitative and quantitative exposure judgements are reasonably accurate (21).

The European standard EN689 was developed in 1995 (103) and updated in 2018 (104) to harmonize methods to assess compliance with occupational exposure limits for exposures to airborne substances in workplaces. The compliance assessment of workers' exposures is performed for each SEG through the application of several standardised tests. D'Errico et al (105) recently compared the two versions of EN689 using 1383 respirable dust measurements collected amongst 867 workers and found that the 2018 version of the standard was considerably more stringent and resulted in more non-compliant SEGs than the 1995 version of the same standard. The authors concluded that the limited number of measurements proposed in the original EN689 could easily result in more doubtful exposure decisions, and incorporating an individual compliance test that takes into account between-worker differences in exposure into the next version of EN689 will result in even further improvement (105).

In the Australian context, the AIOH *Occupational Hygiene Monitoring and Compliance Strategies* document (106) outlined a strategy focused on compliance decision making. The basic tools and concepts of the strategy are used to make the conventional assessments of exposure for assessing the level of health risk or tracking trends in exposure (106). Such issues as SEG identification, location and duration of sampling, number of measurements required, random sampling, and statistical analysis are discussed. A second group of tools comprise of processes for determining regulatory compliance, which follows the modern approach of comparing the entire exposure profile with a regulatory standard (106). The issues of statistical and compliance testing are discussed at length.

Similarly, the document *Testing Compliance with Occupational Exposure Limits for Airborne Substances* (107) developed jointly by the BOHS and the Dutch Nederlandse Vereiniging voor Arbeidshygiene (NVvA) provide guidance to hygienists on measurement strategies for determining compliance with occupational exposure limits. The strategy has five steps:

1. Divide the workforce into SEGs
2. Take three representative personal exposure measurements from random workers in the SEG. If all three exposures are <0.1 x OEL, it can be assumed that the OEL is complied with. If at this stage or any later any result is >OEL, the OEL is not complied with
3. Do a *group compliance* test. Take at least six more samples from the SEG, at least two per worker from workers picked at random. Use all nine (or more) samples to apply a test which establishes, with 70% confidence, that there is <5% probability of any random exposure in the SEG being >OEL
4. Do an analysis of variance on the nine (or more) results to establish whether the between-worker variance is >0.2 x total variance. If it is, then step five must be added
5. Analyse the nine (or more) results to do an *individual compliance* test. There should be <20% probability that any individual in the SEG has >5% of exposures > OEL (107)

After the five-step strategy is completed, if the OEL is not complied with, further control measures should be applied. If the OEL is complied with, a periodic monitoring programme should be started, with frequency depending on the test results (107).

In recent years, there has been substantial interest and work on developing exposure assessment strategies that evaluate health risks from all substances for all workers for all days instead of a hypothetical maximum risk worker on a single day for substances with legal exposure limits. Such a comprehensive exposure assessment strategy would characterise exposure variability and produce data that can also be used for baseline monitoring, surveillance, deciding whether to start or discontinue specific exposure control measures and for epidemiology. Rappaport et al. (95) proposed classification schemes where either the entire population of workers is randomly sampled and subsequently divided into similar groups or workers in a primary building or with similar job titles are sampled and then divided into groups. These sampling-based approaches require multiple measurements of every sampled worker in an SEG and mixed models to statistically estimate the between and within-worker components of variance and fixed effects that are determinants of exposure. However, this may not always be feasible due to resource constraints. As an example, even a medium-scale manufacturing facility with approximately 100 exposure tasks and approximately 15 to 20 chemicals per task will result in >1500 chemical task combinations (i.e., SEGs) and obtaining multiple measurements from several workers in each SEG could rapidly become infeasible (95).

Another approach centres around the use of self-assessment methods that enable workers to measure their own exposures and thereby reduce the dependence on occupational hygienists for sampling (108-110). However, these are preliminary findings and further research is needed to establish the feasibility of such techniques in a broad range of situations.

2.4 Cognitive biases and heuristics

The study of cognitive mechanisms involved in human decision-making has been a central research topic for psychologists for the better part of the last century and remains in the research focus to date (111). The term most often associated with this field of study is “cognitive biases and heuristics.” In the 1970s, the cognitive psychologists Amos Tversky and Daniel Kahneman published a series of papers, including a widely influential article in *Science* (112) which declared that humans made probability judgements through a series of heuristics which lead to systematic and predictable bias (113). Through their research, Tversky and Kahneman demonstrated that these heuristics were shown to lead to systematic biases, the most popular being the conjunction fallacy, base rate neglect and miscalibration (112, 114, 115). The article in *Science* described three heuristics named representativeness, availability, and anchoring and adjustment.

The representativeness heuristic reflects the assignment of an object or event to a specific group or class of events. If the decision maker lacks relevant experience, a surrogate (and less relevant) memory may be used, such as using a normal distribution rather than a skewed log-normal distribution. The availability heuristic reflects the tendency to equate the probability of an event with the ease with which an occurrence can be retrieved from our memory (116, 117). For example, a hygienist may recall a family member or acquaintance who has suffered an asbestos-related disease, and thus may overestimate the severity of asbestos exposure on those around them. This may lead to a discounting of offsetting information, especially when such data conflict with easily recalled personal experience (118). The degree to which a person's experiences and memory matches the true frequency determines whether these judgments are accurate. The anchoring and adjustment heuristic is a strategy for estimating uncertain quantities (116, 117). When trying to determine the correct value, our minds 'anchor' on an initial value, and then adjust to accommodate additional information. The degree to which our final answer is anchored to the initial value can be influenced by many factors resulting in incorrect conclusions, for instance, the initial value used to anchor against may not be a good approximation of the true value.

Cognitive biases may present when a hygienist is trying to interpret skewed, lognormal distributions which are common in occupational hygiene data (23) (19). Reviewing a lognormally distributed dataset can complicate decisions, and hygienists will often make decisions based on probability and professional judgement. Using heuristics leads to a pattern that assigns weights to decisions that differ from the true probabilities of these outcomes. Improbable outcomes are over-weighted, while outcomes that are almost certain are under-weighted. In addition to this problem, there is another potential challenge for the occupational hygienist who aims to interpret and contextualise occupational noise using the logarithmic scale. Logarithmic scales convert multiplicative relationships to additive ones, providing a way to span many orders of magnitude (119), to show elasticities and other proportional changes (120), and to linearise power laws (121). Outside of occupational noise measurement, logarithmic scales are used in scales of acidity (122), earthquake magnitude (123), star brightness (124), population growth (125), radioactive decay (126) and are frequently used for presenting income (127) and time (119). In addition, logarithms can also assist in the computation of likelihoods (30) and transforming data to fit statistical assumptions (128).

Logarithmic scales have also been demonstrably difficult to interpret (129-132). These difficulties have been documented in high school (129, 131, 132), college (130) students, and practising scientists (133). The issue of misinterpretation may extend out even to scientists who have substantial statistical training and who frequently use and encounter logarithms (133). For example, Menge et al. summarised the extent of log scales in the literature and showed that 22% of papers published in the journal *Ecology* in 2015 included at least one log-scaled axis, of which 21% were log–log displays (133). The authors conducted a survey that asked members of the Ecological Society of America to interpret graphs that were randomly displayed with linear–linear or log–log axes (133). Of the 623 respondents, many more interpreted graphs correctly when the graphs had linear–linear axes (93%) than when they had log–log axes (56%). Based on this, the authors concluded that misconceptions about log scaled data are “rampant” even in a group who are regularly exposed to logarithms. The authors suggest that confusion about log-scaled data is likely to be common among many scientists, not just ecologists (133).

2.5 Accuracy of professional judgement

Professional judgement plays a crucial role in any field in which decisions must be made in the absence of a complete data set (134-136). Medical professionals, weather forecasters, air pilots, financial analysts and occupational hygienists all use professional judgement to facilitate their decision making (21, 115).

For occupational hygienists, professional judgment is commonly used to assess exposures where monitoring data is limited or not yet available. Research to date has indicated that this ‘art’ of making exposure judgments is some combination of professional experiences, educational background and other unknown factors (137-139). As discussed in section 2.4, a key factor relating to the accuracy of professional judgement may be that of cognitive biases which may present when a hygienist is trying to interpret skewed, lognormal distributions which are common in occupational hygiene data (23) (19). When reviewing these distributions, mental shortcuts, known as heuristics, are often used which can lead to errors in judgment and introduce bias (116, 117).

Several studies have been published on the accuracy of professional judgment in occupational hygiene (136-138, 140-142); however, the results from research specifically testing hygienists' exposure estimates against exposure measurements have been variable. Hygienists' judgements were often more accurate when exposure measurements were made available to act as a reference point or anchor to their own exposure estimates (143). This finding is not unexpected, given the 'anchoring and adjustment' heuristic is a known cognitive strategy for estimating uncertain quantities (116, 117), meaning that when trying to determine the correct value, the mind will 'anchor' itself to a specific value, and then adjust to accommodate additional information.

While hygienists' estimates are often poorly correlated with exposure measurements, hygienists have been able to successfully rank the order of exposed jobs (144-146). Many epidemiological studies are now assessing the validity of the expert exposure ratings prior to their use (145, 147).

Most exposure judgments made by hygienists are qualitative and can often be the determining factor as to whether any measurements should be made. Low accuracy of these judgments can therefore lead to incorrect follow-up activities, which may place workers at risk. Recent findings suggest that the understanding of how workplace factors affect exposure needs to be significantly improved among practitioners (138, 148) and that low accuracy in exposure assessment could be due to occupational hygienists receiving little formal training on how to conduct a basic exposure characterisation (149). If this step of the exposure assessment is not conducted in a systematic way the hygienist may not investigate the exposure that presents the highest exposure potential with enough detail, leading to low judgment accuracy (149).

2.6 Expert elicitation

An expert is commonly defined as someone with comprehensive and authoritative knowledge in an area not possessed by most people (150). Expert elicitation is the process of quantifying expert knowledge in a particular area or domain, and can be quite useful when empirical data is limited, unreliable, expensive to obtain, or otherwise unavailable (151). The solicitation of scientific and technical judgments from experts in the form of subjective probability distributions can be used directly or fitted to formal decision models.

Despite the challenges of cognitive biases described in section 2.4, the use of expert knowledge in decision making has been gaining traction in areas where a traditional approach of using measured data may be problematic (152-154). Expert elicitation has been shown to improve decision making across a broad range of disciplines, including psychology (115, 136), drug delivery and development (155), transdermal delivery and toxicity (156) environmental exposure assessment (157), habitats of rare species (158) and aggregate exposure assessment (159).

One of the most important aspects of an elicitation protocol is the choice of summary statistics used to describe the distribution and the order in which these statistics are elicited (160-162). These summary statistics need to be meaningful to the experts, especially when the experts have limited statistical and probability knowledge (113). From an accuracy standpoint, a number of expert elicitation studies comparing subjective judgement to measured data (152-154) have suggested that experts are typically able to estimate the range of measured data distribution quite accurately, however the most common value tends to be higher than the measured value.

Expert elicitation appears to be a suitable fit for the profession of occupational hygiene because the underpinning science is both pragmatic and practical (56). Unlike other scientific endeavours, occupational hygiene research topics are often identified through direct human experience in the workplace, and the results of the research are often immediately applicable to the solution of a problem (56). In problem solving, the tacit knowledge underlying expert elicitation can be very valuable (163, 164). However, the use of expert elicitation in the occupational hygiene profession has had mixed results. Ramachandran et al. (165) concluded that subjective expert elicitation concerning nickel speciation is at least as precise as sparse measurement data and that there is a body of specialised knowledge that experts draw on to reach similar judgements. In another study assessing the risk of mesothelioma development from exposure to chrysotile asbestos, Hodgson et al. (166) identified that the analysis of lung cancer risk from data collected in a study of asbestos related mortality (167) was nearly identical to data sourced from expert 'best estimates' in an earlier meta-analysis (168). In contrast, Friesen et al. (169) found only moderate correlation between expert elicitations and exposure to coal tar pitch volatiles, and concluded that even when exposure measurements are available, the expert elicitations are significantly different than measurement-based exposure assessments. Recently, Williams et al. (37) developed a control banding matrix to provide guidance for employers and others to help assess the risks of COVID-19 infection during the pandemic. The matrix was based on occupational hygiene principles and the judgement of the occupational health experts involved since objective data on workers' exposure were unavailable. The data from the study suggested that the highest exposure ranked jobs were associated with higher age-standardised mortality; however, there was considerable variability in exposure elicitations between the experts, which led the authors to assign the control guidance as 'precautionary' with a need for more testing to be conducted (37).

2.7 Statement of research gaps

As outlined above, accurate exposure judgments are the foundation of efficient and effective exposure management. The concept of professional judgement underpins the way in which an occupational hygienist assesses an exposure problem; however, despite the importance placed on professional judgement in the discipline, a method of assessment to characterise subjective judgement accuracy has not been available. Further, there is a need for research to be conducted which directly compares expert judgements to the equivalent measured data to assess quality, validity and accuracy of the individual experts and to compare this between experts. In addition, the few studies assessing judgement accuracy and decision making in hygienists have been limited to mostly chemical exposures (23, 24, 54, 165). As of writing, no studies assessing judgment accuracy for the hazard of occupational noise – a ubiquitous and pervasive risk to worker health - have been available.

For hygienists who may have limited resources to undertake multiple, full-shift samples, task-based exposure assessment may be a useful tool; however, the utility of this form of sampling is still yet to be proven consistently, and research directly comparing ‘like-for-like’ real time values with full-shift sampling is needed.

Finally, the principal goal of the occupational hygienist is to protect all workers by reducing workplace health risks to as low as reasonably practicable, and to do this, the hygienist will call upon standardised tools, guidelines and protocols to assist in decision making and professional judgement (23). The extent to which departure from these norms and established frameworks occurs within the occupational hygiene profession – often referred to as ‘practice variation’ – has not previously been the focus of research. In addition, occupational hygienists regularly make decisions relating to worker exposure based on professional judgement, usually in the absence of quantitative data and in the presence of high uncertainty (24). These factors have the potential to lead to bias and error. Research focussing on understanding current process, decision making, and any variation from standard work practices in relation to exposure assessments undertaken by practising hygienists is needed to assess whether a) this is a problem in the profession, and b) which areas of practice this applies to.

Chapter 3: Description of experience and current practices with respect to professional practice and judgement

This chapter presents the findings of a survey undertaken by occupational hygienists focusing on current practice, with a specific focus on exposure assessment and decision-making. The questionnaire, participant information, and consent form can be found in Appendix D.

This chapter was presented as a paper at the 39th Annual Conference and Exhibition of the Australian Institute of Occupational Hygienists (AIOH) held in Brisbane from 3 to 7 December 2022. A copy of the relevant excerpt from the AIOH 2022 conference proceedings can be found in Appendix E.

3.1 Introduction

The definition of occupational hygiene, centred around the tenets of anticipation, recognition, evaluation and control (29), speaks to the complexities and diversity within the profession. The practicing hygienist will be expected to do many things; however, the ‘evaluation’ component of a hygienist’s role directly relates to the concept of exposure assessment (21). Occupational hygienists work across a diverse range of industrial environments and encounter a broad range of exposure problems. The hygienist will call upon standardised tools, guidelines and protocols, as well as professional judgement – the deployment of subjective reasoning based on experience and intuition - to come to a decision about the impact of the work environment (22). These exposure decisions are often made in the absence of quantitative data and in the presence of high uncertainty (54).

In addition, the practice of occupational hygiene has spread beyond traditional industrial settings and hygienists are increasingly involved in broader fields of practice (34, 170). The traditional ways in which an occupational hygienist approaches their work, particularly in the areas of measuring and monitoring, are also changing. There has been a decline in occupational hygienists employed by industrial corporations and an increase in the outsourcing of occupational hygiene expertise to consultancy companies (55, 170). There has been a rise in the tendency to out-source occupational hygiene-related activities and with this has come a corresponding rise in occupational hygiene consultancy (55, 170). The practical implication of this has meant a reduction in baseline-type sampling programs (which use randomisation and full-shift sampling methods to describe a worker’s exposure to a hazardous agent), and an increase in shorter sampling campaigns that yield fewer data points on which to make exposure decisions. This puts a higher onus on the importance of accurate professional judgements to fill in any ‘gaps’ in quantitative data to adequately protect the worker. These factors have the potential to lead to heterogeneity between practitioners, bias, error and practice variation in the form of deviation from established guidelines or protocols.

Occupational hygienists have access to several strategies and practices to assist in the goal of exposure assessment. Many of these strategies are focused on compliance, whereby a maximum-risk worker is assessed to determine whether exposures are above or below an established limit (21). However, more contemporary strategies have begun to focus on a more comprehensive exposure assessment, which emphasises characterisation of all exposures for all workers on all days (21, 97). Currently, we do not have an overview of which strategies and tools are most used by practicing occupational hygienists, or whether these practitioners agree with the utility of these exposure assessment strategies given their own experiences.

Given these issues, particularly in light of the increasing diversification of the profession, we surveyed occupational hygienists to understand three key areas of practice: experience and work history, professional judgement and decision making, and current practice approaches. It is hoped that the outcomes of this research can help inform future training and education programs for practicing occupational hygienists to help them better navigate the challenges described.

3.2 Methods

Data for this study were collected through an anonymous online survey which took place between 1 May and June 30, 2021.

3.2.1 Recruitment procedure and data collection

The opportunity to complete the online questionnaire was offered to members of three professional bodies – Australian Institute of Occupational Hygienists (AIOH), British Occupational Hygiene Society (BOHS), and American Industrial Hygiene Association (AIHA) – via each institute's social media platforms (Twitter, LinkedIn). Consent was gained from each respondent prior to completion of the survey. Data collection was carried out with a secure hosting server and the survey software Qualtrics XM, (www.qualtrics.com), which ensured data and participant protection including confidentiality, anonymity and withdrawal. The online survey could be completed at the workplace or at home, and the participant could withdraw at any time during the process. Participants were incentivised through the opportunity to receive a cash gift voucher, which was in line with the ethics approval for the study. The Curtin University Human Research Ethics Committee approved this survey (Approval number HRE2021-0156).

The survey was divided into three sections: experience and work history; professional judgement and decision making; and current practice approaches.

For experience and work history, the following information was collected: current job descriptor; length of practice; age group; employment sector; employment industry; certification status; whether the participant had presented a paper at a conference; whether the participant had published a paper; tertiary education level; whether risk communication training had been undertaken; whether data interpretation training had been undertaken; and whether they had received any technical mentoring.

With respect to exposure assessment experience, the following information was collected: percent of time using professional judgement to assess exposure risk; percent of time focused on exposure assessment; and experience in dealing with 'high stakes' risk communication (including but not limited to expert witness testimony, community outrage, adverse media attention, and industrial relations issues).

To ascertain key decision-making factors, the following information was collected: decision making approach utilised (intuitive vs analytical); whether approach is altered based on agent; whether approach is altered depending on size of organisation; whether ethical issues are considered during approach; level of comfort in making exposure judgements in the absence of quantitative data; level of comfort in communicating exposure risk in the absence of quantitative data; use of heuristics as a decision-making tool; and type of heuristic(s) used.

To provide further information on current exposure assessment practices, the following information was collected: tools used to complete an exposure assessment; types of decision statistic(s) used to assess acceptability of exposure; sources of information relied upon to make an exposure judgement (in the absence of measured data); and resources used to complement professional judgement.

For the exposure assessment strategy question, a framework was provided detailing key steps based on the AIHA, AIOH and BOHS strategies (21, 106, 107). The hygienists were asked to review the exposure assessment framework, identify a level of agreement, and provide comment on how this strategy could be improved.

To gain an understanding of exposure assessment motivation and intent, an open-ended question was included: "What goal/s are you looking to achieve when you complete an exposure assessment?'.

3.2.2 Data analysis

Frequencies and percentages were used to describe the data for the categorical variables.

Free text responses were converted into digital text and categorised under major themes within the data. The text data were analysed using NVivo 9 (QSR International, 1999-2011), a qualitative data management software package. In the results below, quotations in the respondent's exact words are used to illustrate causal attributions. The examples were chosen to demonstrate themes and are not necessarily representative of all respondents.

3.3 Results

The results section is divided into three sections: experience and work history; professional judgement and decision making; and current practice approaches.

3.3.1 Experience and work history

A total of 189 responses were collected. Respondents came from 18 countries, the highest numbers coming from Australia (*n* = 83), United States (*n* = 45), United Kingdom (*n* = 26), Canada (*n* =11), and South Africa (*n* = 5). Fewer than 5 responses were received from the following countries - Belgium, Botswana, Ghana, India, Indonesia, Mongolia, Peru, Qatar, Spain, The Netherlands, Zambia, Kuwait, and Oman. The most common job role descriptor reported was that of ‘occupational hygienist’ and there were wide ranges of ages and durations of practice (Table 1). Most respondents were employed in the private industry and consultancy sectors, and the most common industries were mining and manufacturing. About half the respondents were certified hygienists, and risk communication training, data interpretation training and technical mentoring had each been received by over half the respondents.

Table 1 Demographic and occupational characteristics of responding occupational hygienists

Question parameter	Options	*n*	% Response
Current job descriptor	Occupational Hygienist	79	57.6
	Health, Safety & Environmental Professional	28	20.4
	Consultant	15	11
	Other	15	11
Length of practice	<5 years	27	19.3
	5 – 10 years	47	33.5
	10 – 20 years	33	23.5
	>20 years	33	23.5
Age bracket	20 – 30 years	22	15.7
	30 – 40 years	51	36.4
	40 – 50 years	37	26.4
	>50 years	29	20.7
	Prefer not to say	1	0.7
Employment sector	Private industry	74	52.5
	Consultancy	41	29.1
	Government	15	10.6
	Academia	5	3.5
	Other	6	4.2
Employment industry	Mining	41	25.4
	Manufacturing	30	18.6
	Oil and Gas	18	11.2
	Construction	14	8.7
	Chemical	7	4.3
	Agriculture	4	2.5
	Other	47	29.2
Certified hygienist status	Yes	68	48.5
	No	72	51.4
Presented at a conference	Yes	84	60
	No	56	40
Published a paper	Yes	51	36.4

	No	89	63.5
Tertiary education level	Bachelors degree	38	27.7
	Masters degree	69	50.3
	Doctor of Philosophy	14	10.2
	Other	16	11.7
Risk communication training	Yes	90	64.7
	No	49	35.2
Data interpretation training	Yes	74	53.6
	No	64	46.4
Technical mentoring received	Yes	71	51.1
	No	68	49

3.3.2 Professional judgement and decision making

Most respondents reported spending between 25 – 50% of their time using professional judgement to assess exposure risk and focused on exposure assessment (Table 2). Over half of all respondents reported being 'somewhat experienced' when asked to describe their experience in dealing with 'high stakes' risk communication.

Table 2 Exposure assessment experience of participants

Question parameter	Options	*n*	% Response
Percent of time using professional judgement to assess exposure risk	<25%	33	30.5
	25 – 50%	41	38.0
	50 – 75%	21	19.4
	>75%	13	12.0
Percent of time focused on exposure assessment	<25%	27	25.0
	25 – 50%	39	36.1
	50 – 75%	29	27.0
	>75%	13	12.0
Experience in dealing with 'high stakes' risk communication	Very experienced	18	16.6
	Somewhat experienced	67	62.0
	Never undertaken	23	21.3

The decision-making section of the questionnaire encouraged respondents to qualify their approach to reasoning and judgement with respect to exposure assessment. When asked to describe their approach to occupational hygiene decision making, most respondents reported being 'analytical and conscious' when compared to being 'intuitive and subconscious' (Table 3). Most respondents indicated that they would change their exposure assessment approach depending on the agent of interest, with most also reporting that they would change their assessment approach depending on the size of the organisation. From an ethical standpoint, almost all respondents (83%) indicated that they definitely or probably would consider ethical factors when undertaking an exposure assessment. Most respondents (72.4%) expressed being extremely or somewhat comfortable when making exposure judgements in the absence of quantitative data. When asked to report on level of comfort in communicating exposure risk in the absence of quantitative data, most

(77.8%) reported that they were extremely or somewhat comfortable. The deployment of heuristics to aide decision-making was reported to be ‘used occasionally’ by most respondents. When asked to identify which heuristics the respondent recalls having used, most respondents expressed the use of the ‘availability’ and ‘representativeness’ heuristic.

Table 3 Decision making factors of occupational hygienists

Question parameter	Options	*n*	% Response
Decision making approach	Intuitive and subconscious	12	11.3
	Analytical and conscious	94	88.7
Alter approach based on agent	Yes	83	77.5
	No	24	22.4
Alter approach depending on size of organisation	Yes	63	60
	No	42	40
Ethical considerations considered	Definitely yes	62	58.5
	Probably yes	26	24.5
	Might or might not	15	14.1
	Probably not	3	3
	Definitely not	0	0
Comfort in making exposure judgements in the absence of quantitative data	Extremely comfortable	13	12.4
	Somewhat comfortable	63	60
	Neither comfortable nor uncomfortable	16	15.2
	Somewhat uncomfortable	13	12.4
	Extremely uncomfortable	0	0
Comfort in communicating exposure risk in the absence of quantitative data	Extremely comfortable	23	22.1
	Somewhat comfortable	58	55.7
	Neither comfortable nor uncomfortable	14	13.4
	Somewhat uncomfortable	8	7.6
	Extremely uncomfortable	1	0.9
Use of heuristics as a decision-making tool	Used regularly	20	19.4
	Used occasionally	67	65
	Never used	16	15.5
Heuristics used	Anchoring and adjustment	14	17.1
	Availability	34	41.4
	Representativeness	34	41.4

3.3.3 Current practice approaches

The sources of information used by occupational hygienists to make exposure judgements in the absence of measured data included the walkthrough survey

(27%), review of existing controls (16%), and peer reviewed literature (12%) as being the top three sources of information (Figure 2).

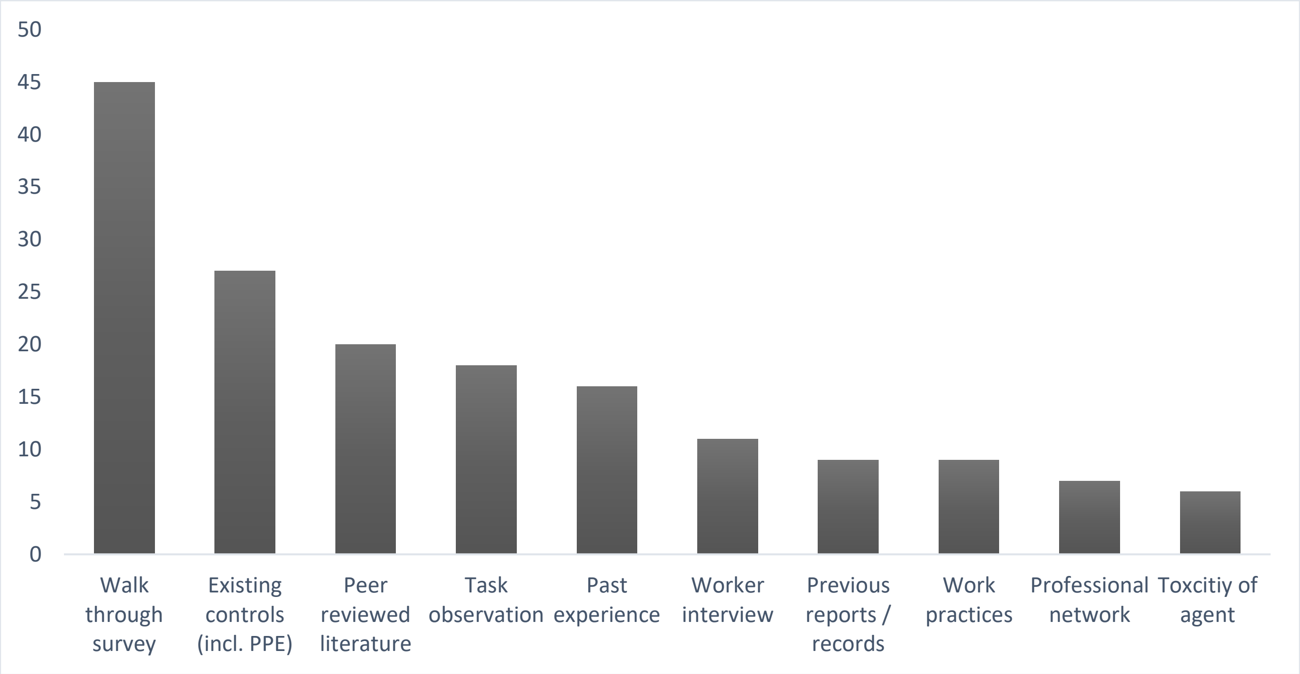

Figure 2 Top 10 sources of information used by participating occupational hygienists when making an exposure judgement in the absence of measured data (participant numbers are denoted on the Y axis)

Decision statistics used by occupational hygienists when assessing measured data included use of the 95th percentile (14.5%), geometric standard deviation (12.5%), and percentage over OEL, minimum, and maximum result (11% respectively) as the top three decision statistics used when assessing measured data (Figure 3).

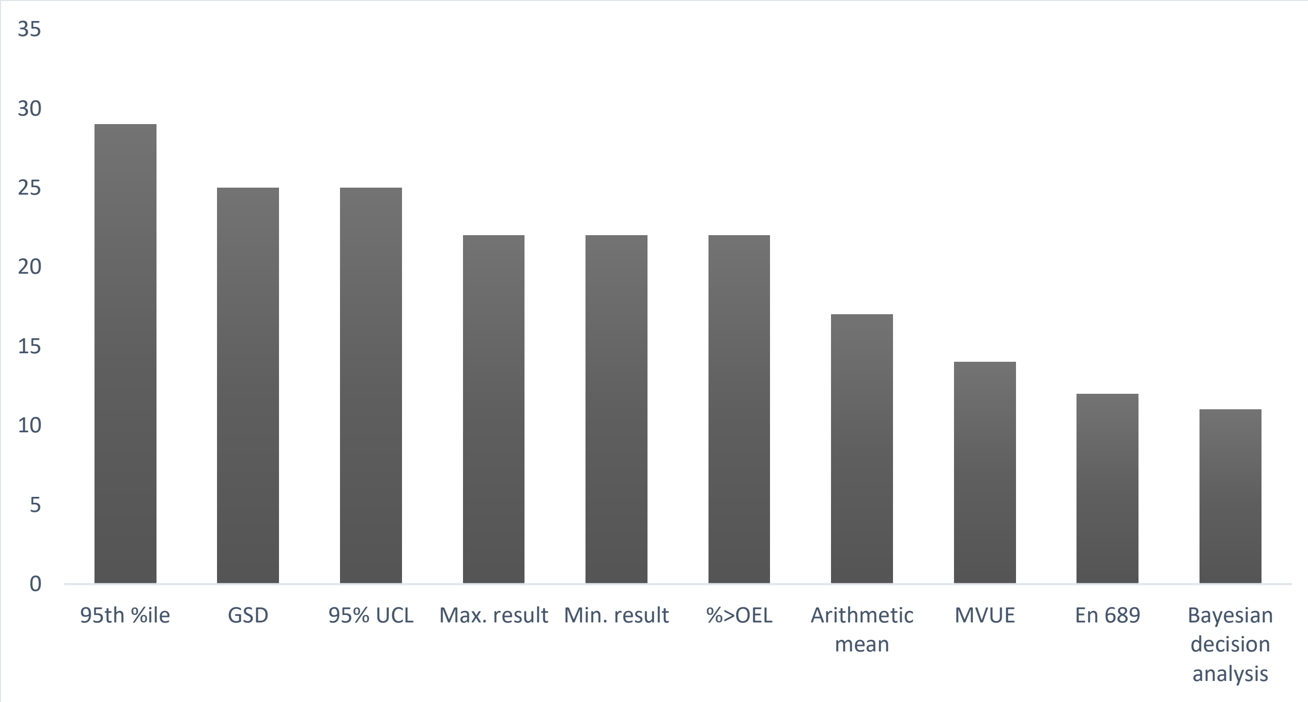

Figure 3 Top 10 decision statistics used by participating occupational hygienists when assessing measured data (participant numbers are denoted on the Y axis)

Figure footnote - %>OEL = percent of samples above the relevant occupational exposure limit; 95% UCL = 95% upper confidence limit; MVUE = minimum-variance unbiased estimator; 95th %ile = 95th percentile; GSD = geometric standard deviation; EN 689 = European Standard Workplace exposure – measurement of exposure by inhalation to chemical agents – Strategy for testing compliance with occupational limit values

When completing an exposure assessment, the top three tools used were direct task observation (26%), air sampling (15%), and IHSTAT (12%) (Figure 4).

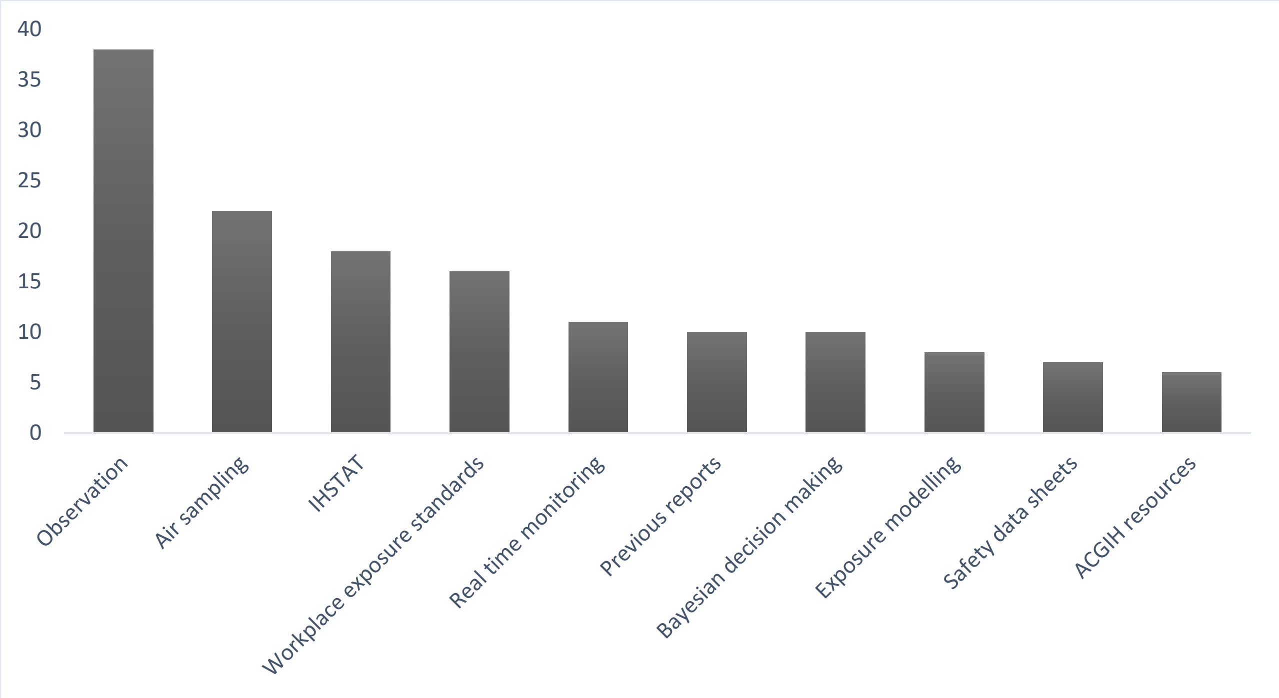

Figure 4 Top 10 tools used by participating occupational hygienists when completing an exposure assessment (participant numbers are denoted on the Y axis)

Resources used to complement professional judgement were a combination of all suggested (25%), technical papers (23%), peer reviewed journals (22%), government websites (17%), and professional networks (10.5%) (Figure 5). Other sources mentioned in the free text answers included industry standards and the internet.

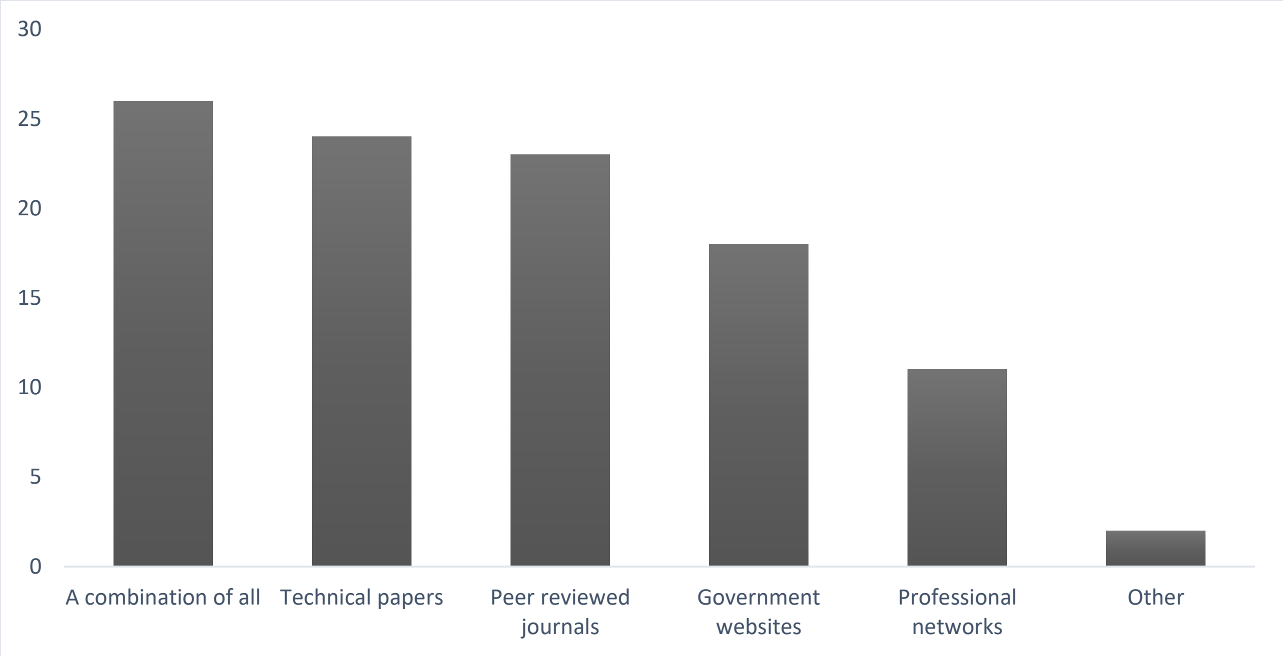

Figure 5 Resources used by participating occupational hygienists to complement their professional judgement (participant numbers are denoted on the Y axis)

3.3.4 Agreement with proposed exposure assessment strategy

Most respondents were in strong agreement with the standardised exposure assessment strategy framework (Table 4).

Table 4 Agreement with proposed exposure assessment framework

Standardised exposure assessment strategy framework	Options	*n*	% Response
1. Identify the Similar Exposure Group (SEG) to profile **2. Randomly select workers and exposure periods within the selected SEG** **3. Collect samples of the randomly selected workers at randomly selected time periods** **4. Calculate the descriptive statistics for the data set** **5. Determine if the data fits a lognormal and/or normal distribution** **6. Make a decision on the acceptability of the exposure profile** **7. Refine the SEG, if necessary** 8. **Advise on control based on exposure profile acceptability**	Strongly agree	61	56.5%
	Somewhat agree	39	36.1%
	Disagree	8	7.4%

Although half of the respondents ‘strongly agreed’ with the framework, 36% ‘somewhat’ agreed, and 7% ‘disagreed’. A breakdown of the responses shows that those who responded positively were employed by private organisations (potentially well-resourced) and those less supportive worked in the consultancy sector.

In the open-ended follow up question “For the previous question, if you answered, ‘somewhat agree’ or ‘disagree’ how would you improve upon the exposure assessment process?”, four major themes were identified within the data – removal of randomised sampling (Step 4), improvement in hazard identification, inclusion of task-based exposure monitoring, and organisational barriers such as resourcing and funding.

Almost half of the respondents who provided a response to this question challenged the need for randomised selection of workers, opting instead to conduct ‘worst case’ sampling. For many of the respondents, these comments were attributed to practicality, time and cost implications.

> *“Remove random selections. Consulting typically requires a worst-case approach. Clients do not have the funds to do randomized studies with sufficient populations to give statistical validity”.*
>
> *“Often as a consultant you only do minimal personal monitoring so you tend to measure a near worse-case scenario which biases the result, but you can be confident that the risk is not higher”.*
>
> *“Time periods would not be randomly selected if I was trying to capture exposure during a certain task that a worker is concerned about”.*
>
> *“Needs to have feasibility in there - randomness is great but not always practicable”.*

A substantial number of respondents described the need for improvement in basic hazard characterisation to be included within the process.

“Understand the exposure control measures in place prior to undertaking the exposure assessment. If control measures are insufficient then pause the exposure assessment and focus on exposure control as a priority”.

“In field visual inspection and qualitative assessment prior to sampling”.

“A walkthrough to determine any immediate actions needed and understanding what the customer (internal or external wants from the OH)”.

Several respondents suggested task-based monitoring as an improvement to the framework.

“Ensure work task is representative of the exposure. Some work tasks vary based on production and scheduling that changes”.

“I love the process. I just find in reality it is very hard to define SEGs. I end up assess exposure profiles based on task and I usually never have enough data to truly get good analysis.

“I don’t find SEG based monitoring all that useful. For me, task-based exposure monitoring is the best way to identify your exposure sources and recommend controls”

“Hygienists need to embrace real-time monitoring. Although I would say a limitation with this is the lack of formal or technical guidance for this. Also, regulators would need to catch up on this as it is a very new area for hygiene”

A number of respondents reported potential roadblocks to the process in the form of organisation size, availability of resources and funding.

“An ideal approach but needs to be balanced against ‘real world’ challenges such as cost”.

"This approach only works in mining and oil and gas with large workforces who monitor regularly. It doesn't work for a small 5-person workforce that does an assessment every 5 years or less".

"I agree very much with this process, however budget may dictate what is actually achieved. I would also suggest that larger companies are better placed to follow the correct process to ensure adequate exposure profiling".

3.3.4 Goals of exposure assessment

In the open-ended follow up question "What goal/s are you looking to achieve when you complete an exposure assessment?", key themes identified within the data were – accuracy, representativeness, statistical confidence, control identification, exposure magnitude, exposure source(s), quantitative data, health risk evaluation, compliance, communication, and disease prevention.

Two thirds of the respondents reported the importance of 'accurate' and 'precise' outcomes in exposure assessment to best protect workers.

"Accurate reflection of credible exposure for worker and workers, understanding exposure pathways and associated control utilisation".

"Accurate delineation, explanation, and assessment of exposure".

"Capturing accurate data to present effectively to stakeholders".

"Make a precise and representative as possible assessment (closest to reality) to give people an insight in contribution to relevant health effects".

The need for data to be statistically reliable featured in a quarter of responses.

"To assess with statistical confidence, to what degree exposure to the hazardous agent is likely to cause adverse health effects".

"Achievement of accurate data, statistical confidence, but above all - receipt of the data by the target audience as legitimate and accepted, based on the science and not skewed based on bias, or perception of risk".

"Data to be statistically meaningful".

Compliance was a strong theme for around one third of participants.

> *"To comply (and to be able to demonstrate such compliance) with the Work Health and Safety Regulations and other relevant legislative requirements".*
>
> *"Education and Compliance".*
>
> *"Compliance with legislation".*

Control identification was a theme identified by around half of respondents.

> *"Review existing controls and their effectiveness".*
>
> *"Identify hazards and appropriate controls".*
>
> *"Determine the risk of exposure to an agent, identify if controls are effective of if further controls are required".*

Communication, worker engagement / feedback and prevention of ill health and disease were also a feature of approximately two thirds of responses.

> *"Understand the work environment including types of tasks and potential exposures, quantify worker exposure through the collection of statistically significant data, review existing controls and their effectiveness, provide feedback to workers and develop a report detailing findings including control recommendations to address issues identified".*
>
> *"To document exposures and control efforts and communicate exposure assessment findings to all affected workers and those involved in worker health protection (e.g.: management, medical staff, and engineering staff)".*
>
> *"Use information for regulator and employee feedback".*
>
> *"Identification and communication with key stakeholders, assessment, monitoring plan, data review, communication, review with key stakeholders, path forwards".*
>
> *"Risk to health from exposure, determining biological monitoring, ensure adequate protection, regulatory compliance".*
>
> *"Quantify exposures, identify exceedances and any risk to health, assess effectiveness of controls".*

3.4 Discussion

Our findings highlight the heterogeneity of current practices between occupational hygienists and provide insight into professional judgement and decision-making approaches. The outcomes identify areas for which capability of professionals could be improved through mechanisms such as web-based training, workshops, seminars, and other educational materials. Findings also suggest ways to improve exposure assessment through the integration of real time monitoring, task-based exposure assessment, and improvement in basic hazard characterisation. An opportunity exists to update existing protocols and create technical guidance across these areas to enhance continuous improvement within the profession.

The survey results serve as perhaps the first published study focusing on occupational hygienists and their practices. As this study has demonstrated, practitioner feedback may be used to highlight which standardised strategies and tools are working well, and which aren’t, presenting professional occupational hygiene associations with opportunities to update these documents based on feedback. Regular surveys may assist in building upon current practice and provide the requisite level of introspection needed to ensure that the profession is well positioned to support the changing work landscape which was detailed in Chapter 1. Information may also be gleaned from practitioners by focus groups or committees led by professional occupational hygiene organisations, with the resulting information being used to inform education and awareness program.

The decision-making section of the questionnaire encouraged respondents to qualify their approach to reasoning and judgement with respect to exposure assessment. Occupational hygienists will synthesize a high volume of information to inform their decision-making, sometimes through complex, cognitive tasks representative of conscious decision-making in addition to intuitive or emotional decision making (171). Most respondents identified their decision-making approach to be ‘analytical and conscious’, when compared to the option of ‘intuitive and subconscious’. This finding may be indicative of how hygienists see themselves and their role when compared to their peers working across the disciplines of health, safety and environment. The work of a hygienist is typically referred to as the scientific side of safety (10, 29) and so when given the option between analytical and intuitive, a hygienist may be more inclined to nominate a response that is most in line with their own self-perception of their role.

Another aspect of decision-making proposes that a limited number of simplifying heuristics are used to efficiently arrive at a judgment using available information (115, 136). These heuristics do not typically utilise all available information and data in a formal algorithmic process but instead use quick and efficient rules of thumb to arrive at a judgment (23, 54). Most respondents reported that they occasionally used heuristics as a decision-making tool, with 16% of respondents reporting that they have never used a heuristic to arrive at an exposure judgement. Given the ubiquitous nature of the use of heuristics, this result may be more indicative of the lack of general awareness of heuristics and therefore an inability to recall their use (115). When asked to identify which heuristics had been deployed, nearly half of the respondents reported use of the availability and representativeness heuristic, with a smaller number (17%) reporting use of the anchoring and adjustment heuristic. A definition of each type of heuristic was provided to the responding hygienists within the questionnaire.

From an ethical standpoint, most respondents would definitely consider any ethical implications when completing an exposure assessment, with 25% probably taking this factor into consideration. All three professional bodies who assisted in disseminating the survey place a large emphasis on ethics as part of membership (including targeted ethics training and education sessions) and so this concept would be well known to hygienists who are members of these organisations (172). Smaller proportions of the respondents indicated that they ‘might or might not’ and ‘probably not’ (14% and 3% respectively) consider ethical implications, despite this focus on ethics by the governing bodies of which all respondents were members. These results indicate a level of deviation away from expected norms around ethics from the respondents.

Most respondents expressed being ‘somewhat comfortable’ in making an exposure judgement in the absence of quantitative data. In terms of communicating an exposure risk in the same absence of quantitative data, over half of the respondents were ‘somewhat comfortable’ and 22% were ‘extremely comfortable’.

A key observation from this study was the variation from the proposed exposure assessment framework based on key elements of the AIHA, AIOH and BOHS strategies (21, 106, 107). Although over half of the respondents ‘strongly agreed’ with the framework, 36% ‘somewhat agreed’, and 7% ‘disagreed’. Notwithstanding this, the result highlights a challenge for the profession in that just under 50% of the respondents did not report full agreement with a standardised, well-known and established protocol.

The major themes identified through the follow up question on the reasons for disagreement with the protocol provide some important issues to consider. The first theme centred around the concept of randomised sampling, which almost half of the respondents reported to be of little utility to their current practices. The reasons provided ranged from the practicality and challenges of randomising the sampling program through to funding constraints which limited the amount of data that can be collected. Most respondents reported that they would preferentially select ‘worst case’ over randomised sampling, the presumption being that the upper bound of an exposure profile would provide the requisite information to inform a required control intervention. The second theme indicated the need to improve basic hazard characterisation prior to sampling – a step referred to in the occupational hygiene profession as a ‘walkthrough survey’ (29). The primary reason indicated was to understand current controls and to solve any acute, or imminent, issues that may be present within the workplace. Task based exposure monitoring, wherein samples are collected based on specific duties undertaken by the worker as opposed to full shift sampling (173), presented as a third theme for improvement. In this case, the respondents mentioned difficulty in defining SEGs within their workplace, and so preferred a more targeted approach to sampling, sometimes using real time sensor technology. The fourth theme centred around organisational factors, such as availability of resources and funding, which limited the ability to follow a defined process.

A key implication of this study is the contrast between practitioner guidelines for exposure assessment and what hygienists do in practice. An example of this is the insight that traditional requirements for randomised sampling hold little appeal for many respondents on account of the complexities and constraints associated with successfully executing true randomisation. Equally, the dynamic nature of some workplaces and job roles meant that many of the responding hygienists felt a need to explore concepts more likely to provide useful exposure information, such as real-time and task-based monitoring. In this regard, the implication for task-based monitoring within the profession is twofold; first, it presents the hygienist who is time and resource poor with a means to quantify exposures outside of the standardised, full-shift model of exposure assessment. Second, it may in fact be a more useful categorisation of the exposure in question and may avoid some of the limitations associated with full-shift, TWA sampling, the most notable example being the single result provided, leaving potential for dangerous, short-term ‘peaks’ in harmful exposure to go unseen.

A potential limitation of this study was the small number of hygienists recruited for participation, a total of 189 respondents of a total membership of approximately 12,000 people (combined membership base of AIOH, BOHS and AIHA) (174-176). In addition, a convenience sampling strategy with social media was deployed to collect data. Future research involving the surveying of occupational hygienists may consider randomised, stratified sampling methodology to provide a better generalisation of results, increase sample size, and minimise bias.

Another potential limitation of the study was that the authors did not investigate whether the variation observed was warranted. Not all variation is bad, and in some cases, may be warranted (177). For example, as previously discussed in Chapter 1 (Section 1.2) current workforces are now much more dynamic and are expected to complete multiple tasks across different work environments which change regularly (28). The concept of full-shift personal monitoring to define the exposure profile of a job role may not be an optimal approach, hence a variation to occupational hygiene practice is appropriate. However, unwarranted variation may also be reflective of structural factors, meaning that some hygienists have less access to certain tools or resources when compared to others. In other cases, variation may reflect evidential uncertainty as to which type of control intervention is best, or may result in a misallocation of resources, which in some areas may be scarce. Future work in this area should consider the distinction between warranted and unwarranted practice variation, and to determine under which circumstances these distinctions occur.

3.5 Conclusion

The results in this study suggest that practice variation in exposure assessment exists amongst occupational hygienists, with the primary findings being that hygienists use different strategies, and that deviations are largely driven by practical considerations like budget and site inspection findings. These findings suggest that further assessment of the extent to which variation exists is needed, and further efforts should assess occupational hygienists' decision-making processes and attitudes when deviating from established guidelines or protocols. Longer term, development of methods and frameworks to a) determine when variation is unwarranted and change is justified, and b) provide facilitated feedback and continuous quality improvement, should be considered to address unwarranted variation in occupational hygiene practice.

Given the sample size of the survey and diversity in the respondents, there was a conscious effort to not overgeneralise or overemphasis the results. However, based on the survey results, it is recommended that a community of practice be established for hygienists to work on a consolidated approach to exposure assessment to reflect the changing landscape of work, considering the insights from this study. Representation from multiple countries is recommended, with a view of creating a blueprint that may be adapted to accommodate for local legislation (for example, provision of real time monitoring that sits adjunct to full-shift compliance monitoring). University curriculums and professional development programs for hygienists should also endeavour to integrate this information to satisfy the changing needs of the practicing occupational hygienist.

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Chapter 4: Occupational noise exposure of utility workers using task based and full shift measurement comparisons

In the previous chapter, task-based exposure assessment was suggested as an improvement opportunity for hygienists who may be limited for time and resources. This chapter presents the findings of an exposure assessment comparison study conducted to determine if a combination of area noise measurements and task activity diaries give a reasonable estimate of full-shift dosimeter measurements in a cohort of utility workers.

The following manuscript was submitted on 4 April 2022 and accepted for publication on 15 June 2022. This chapter presents the accepted version of the following article:

Lowry DM, Fritschi L, Mullins BJ. Occupational noise exposure of utility workers using task based and full shift measurement comparisons. Heliyon. 2022 Jun 1;8(6): DOI: 10.1016/j.heliyon.2022.e09747

It has been published in the final form at: https://www.sciencedirect.com/science/article/pii/S2405844022010350

A copy of the published manuscript can be found in Appendix F.

A summary of this paper was presented at the 37th Annual Conference and Exhibition of the Australian Institute of Occupational Hygienists (AIOH) held in Perth from 30 November to 4 December 2019. A copy of the relevant excerpt from the AIOH 2019 conference proceedings can be found in Appendix G.

4.1 Abstract

Introduction: The main purpose of this study was to determine if a combination of area noise measurements and task activity diaries give a reasonable estimate of full-shift dosimeter measurements in a cohort of utility workers. Few studies have been conducted to evaluate the efficacy of using task-based noise exposures to estimate full shift time weighted average (TWA) noise exposures.

Methods: Estimates of full shift time TWA noise exposures for a group of utility workers (n=224) were calculated using dosimeter measurements. Area noise measurements using a sound level meter were used to recreate the TWA for each personal dosimetry sample based on detail provided in the task activity diary for each sample. Full shift TWA noise exposures were compared to corresponding area noise measurements using simple linear regression analysis.

Results: Associations between full shift TWA measurements and task-based area measurements were closely associated, with R^2 values above 0.85 for all job roles.

Conclusion: Task-based noise exposure analysis has the potential to be widely used in the utilities industry. While full-shift monitoring to determine TWA exposures is useful, the changing work environment, variability in tasks and equipment, and varying workday hours, limit the ability of the 8-hr TWA to accurately characterise the exposures and associated health risks for utility workers.

4.2 Introduction

Exposure to noise constitutes a significant health risk in the occupational environment. There is sufficient scientific evidence indicating that excessive and prolonged noise exposure can induce hearing impairment, hypertension and ischemic heart disease, sleep disturbance and general annoyance (178). A number of studies have also suggested a positive relationship between excessive noise exposure and susceptibility to occupational injuries (179) as well as increased risk of further hearing deterioration (180). In addition, whilst noise is considered a physical factor for damage to the cochlea, combined exposure to noise and certain chemical substances – collectively referred to as ototoxins - can impair the cochlea, the vestibulo-cochlear apparatus, the eighth cranial nerve or the central nervous system (181). Excessive noise exposure in high temperatures may also present a high risk for noise induced hearing loss (NIHL) (182).

Methods for assessing occupational noise exposure have largely focussed on full-shift TWA sampling conducted on workers, however task-based methods have an advantage over full-shift methods in that they provide a more direct understanding of the primary sources of high noise exposure (183). This has a benefit not only in targeting effective noise control interventions in the workplace, but also in estimating exposure levels for a range of task combinations. Task-based measurements can also allow for the characterisation of full-shift exposure whilst also permitting assessment of short-term hazards which might not be identified through a standard full-shift exposure sampling protocol (184). Taking measurements at the task level has been shown to be a useful method for determining hazardous exposures in complex dynamic environments (185). Furthermore, epidemiologic studies benefit from task-based exposure assessments because they support the validity of cumulative exposure histories by limiting misclassifications which can occur when reconstructing past exposures through employment records or work histories (186).

Characterisation of noise exposure for workers who undertake tasks in varied occupational settings and conditions is especially challenging, given the changing work environment in which these professions operate. Therefore, a realistic measure of noise dose utilising full-shift measurements alone would not be expected to be representative of true exposure experienced over a typical shift. In addition, full-shift TWA measurements do not provide information that can be used to identify the source of intense noise exposures experienced. Therefore, determination of noise exposures at the task level for utility workers may be more useful, particularly when developing effective engineering controls to reduce exposure and prevent NIHL. One such group are utility workers, whose highly variable tasks and working conditions present a range of potential occupational noise exposures. Utility workers perform a wide variety of semi-skilled and skilled maintenance duties in the installation, construction, repair, and general maintenance of electrical, water, communications, and power generation assets. Workers who fall into this group are typically trade-qualified and occupy five distinct job roles – electrician, plumber, communication technician, fuel delivery driver and power station operator. In Australia, approximately 144,200 persons were employed in the utilities industry in 2020 (187).

Task based exposure assessment strategies have previously been employed for workplace chemical exposures (184, 185, 188, 189) and occupational noise (190-194). However, only three peer-reviewed studies could be found directly comparing full shift and task-based estimates of exposure to noise (summarised in Table 14). These studies demonstrate that the accuracy of the exposure assessments depend on how well tasks are defined and the ability of statistical models to account for variability in noise exposures. As an example, clearly defining beginning and ending times for each task increases the agreement between estimated and measured daily noise exposures. The studies also indicate there is generally agreement between time-at-task information collected from direct observation and worker self-reports (195-197) Overall, the studies found moderate to good agreement between measured and task-based estimated daily noise exposures.

Table 5 Summary of peer reviewed studies comparing full shift and task-based estimates of exposure to noise

Study aim	Methods and results	Key findings
To evaluate the agreement between task-based estimated and full-shift noise exposures (183).	Task-based noise exposures from 189 subjects on 502 work shifts were used in six linear regression models to obtain estimates of full-shift noise exposures. These models varied in complexity, from estimates using task-based noise exposures alone to estimates using task-based noise exposures grouped by equipment, work location and trade. Agreement between task-based estimates and measured full-shift noise exposures ranged from an R^2 = 0.11 to an R^2 = 0.90.	The study found that the R^2 increases when the specificity of the task definitions increases. This study also found that task-based estimates of full-shift exposure include a high degree of error when the task-based noise exposures are highly variable.
To validate the accuracy of construction worker recall of task and environment based information; and to evaluate the effect of task recall on estimates of noise exposure (195-197).	A cohort of construction workers (n=25) had noise exposures measured by dosimeters, and time-at-task information recorded on activity cards or questionnaires. Simple linear regression was used to determine the agreement between the task-based estimated and dosimetry measured daily noise exposures. The relationship between dosimeter measured daily noise exposures and task based estimated daily noise exposures calculated from activity cards and questionnaires had an R^2 = 0.62, and R^2 = 0.59 respectively.	Six months after tasks were performed, construction workers were able to accurately recall the percentage time they spent at various tasks. Estimates of noise exposure based on long term recall (questionnaire) were no different from estimates derived from daily activity cards and were strongly correlated with dosimetry measurements, overestimating the level on average by 2.0 dB(A).
To compare estimated and measured daily noise exposures (198).	Eight estimates of daily noise exposures were calculated for each dosimeter measured daily noise exposure (n=189). Estimates were calculated using time-at task data collected by direct observation, worker diary, and supervisor summary. Estimated daily noise exposures were calculated using either the arithmetic or geometric mean task-based noise exposures. Agreements between estimated daily noise exposure and measured daily noise exposures ranged from 0.70 – 0.77 for direct observation, 0.63 – 0.71 for worker reports, and 0.49 -0.62 for supervisor assessments.	The study found that a high degree of agreement can be achieved between task-based and dosimetry-based estimates of full-shift exposures. The task-based approach that uses worker reports combined with task AM or GM levels yielded similar results to the more time-intensive direct observation method to estimate full-shift exposures.

The main purpose of this study is to determine if a combination of area noise measurements and task activity diaries give a reasonable estimate of full-shift dosimeter measurement in a cohort of utility workers.

4.3 Methods

4.3.1 Personal noise dosimetry

Personal sampling data were collected with the assistance of personnel from a registered utility responsible for providing the critical services of electrical generation and distribution, water and wastewater, hydrocarbons, and communications to a number of mining operations and five townships located in the Pilbara region in North-Western Australia. The inclusion criteria for this study were personnel employed by the utility in the job categories of electrician, plumber, communications technician, and power station operator. A stratified sampling method was employed and the number of employees to sample was calculated as outlined in Table A-2 of the NIOSH publication *Occupational exposure sampling strategy manual* (19). Personal noise samples were collected and analysed as per *AS/NZS 1269-2005 Occupational Noise Management – Part 1* (199). Workers were selected randomly whenever possible using a random number table.

Equipment used to conduct noise sampling consisted of personal noise dosimeters (type 4448, Brüel and Kjær, Nærum, Denmark) calibrated pre and post sampling with a sound calibrator (type 4231, Brüel and Kjær, Nærum, Denmark). No significant shift in calibration was detected for any individual measurement. The dosimeters measured sound pressure levels in decibels (dB) using an ‘A’ frequency weighting, and the measuring range was 50–140 dB (L_{Aeq}) using no additional threshold level and a 3-dB exchange rate. The dosimeters logged noise data each minute and $L_{\mathrm{Aeq,T}}$ for the total duration of the measurement period was stored. Sampling times were representative of working periods of individuals monitored, which were at least eight hours of a twelve-hour shift. A total of 224 dosimeter measurements were captured.

Participants were instructed to keep track of their activities during the day and to fill out a logbook on their time spent at different tasks during the measurement period. In addition, participants were asked to state their use of hearing protection devices.

4.3.2 Calculation of personal noise dosimetry measurements

For the different job categories the mean $L_{\mathrm{Aeq,T}}$ measured with dosimeters was calculated. Using the equation $E_1 = (10^{(LAeq/10)}) *T$ with L_{Aeq} being the equivalent noise level measured by the dosimeter and T the duration of the dosimeter measurement, an exposure value (E_1) for each dosimeter measurement was calculated. For each job category, the mean $L_{\mathrm{Aeq,T}}$ measured by the dosimeters was calculated using the equation $L_{\mathrm{Aeq,12h}} = 10 * \log((E_1 + E_2 + \ldots)/12h)$, where 12h was replaced with the sum of the durations of the dosimeter measurements in hours. 224 complete and independent full-shift personal measurements were made for the analysis.

4.3.3 Area noise measurements

Area noise measurements were made based on the task details outlined in each corresponding full-shift personal sample to replicate full-shift exposure. Area measurements of noise levels were conducted in accordance with *AS/NZS 1269-2005* (199) using a sound level meter (hand-held analyser type 2250, Brüel and Kjær, Nærum, Denmark). A similar method of sample collection is detailed in ISO 9612 wherein the sound level meter microphone is positioned at the location of the worker’s head during normal performance of a job or task (200).

In each measurement position, 45-second measurements were completed, and A-weighted equivalent noise levels ($L_{\mathrm{Aeq,45s}}$) were recorded. The area measurements were limited to locations where the utility personnel are likely to spend time during the course of planned or unscheduled maintenance work, based on the observations made within the corresponding full-shift measurement task activity logbook. A member of the work group was present at each location to demonstrate typical distances from noise sources. With the worker in position, the sound level meter microphone was located approximately 0.1 m horizontally from the entrance of the external canal of the ear receiving the noise level. The measurement duration of an individual source was sufficiently long for the noise exposure level to be representative of the activities being performed by the worker as required to obtain an L_{eq} reading which had stabilised within ±0.5 dB.

4.3.4 Calculation of area noise measurements

Mean, median and percentiles of noise levels were calculated for each measurement location. The quantity used for averaging the results was calculated from the measured $L_{Aeq,45s}$ by,

$$\frac{p2}{p02} = \left(\frac{L\mathrm{Aeq,45s}}{10} \right) \qquad (1)$$

where p is the sound pressure that corresponds to $L_{Aeq,45s}$ and p_0 is a reference value set at 20 μPa. The corresponding mean sound pressure level was calculated as,

$$\overline{L\mathrm{Aeq,45s}} = 10 \log \left(\frac{p}{p0} \right)^2 \qquad (2)$$

The task based estimated $L_{Aeq,12h}$ was calculated based on mean noise levels during typical working conditions. For each measurement location, an exposure value (E_1) was calculated as,

$$E_1 = (10^{(L\mathrm{Aeq}/10)}) * T \qquad (3)$$

where L_{Aeq} is the mean noise level at the location, and T is the mean hours spent at that location during a 12 hour shift for each job category. The exchange rate used in the equation is 3 dB. $L_{Aeq,12h}$ for each job category was then calculated as,

$$L_{Aeq,12h} = 10 * \log((E_1 + E_2 + \ldots)/12h) \qquad (4)$$

The fit to the data uses the following equation and is calculated as,

$$dB(A)_D = M * dB(A)_T + C \quad (5)$$

Where *M is the slope of the line* and *C* is the intercept. *T* is the mean hours spent at the task location.

4.3.5 Comparison of full-shift dosimeter measurements and area measurements

Each full-shift measurement was broken down to the task level through the review of its corresponding task activity diary. Tasks were assessed in the field using a sound level meter to recreate the exposure measured in the full-shift sample. This exercise was repeated for all personal measurements across all five job roles. An example is shown in Table 6.

Table 6 Evaluation of normalised daily noise exposure using forty five second long average noise levels LAeq,T by observed task activity (Electrician job role example)

Sample 005 – Activity: Asset Inspection and Equipment Repair						
Task	*Measured Noise Level L Aeq,Ti*	*Duration of Exposure Ti*	*Pascal Squared*	*Partial Noise Exposure E A,Ti*	*Total Daily Noise Exposure E A,T*	*Normalised Noise Exposure Level L Aeq,8h*
	dB(A)	*Hours*	*Pa 2*	*Pa 2h*	*Pa 2 h*	*dB(A)*
TP1 inspection - near louvers	88.50	0.15	0.28	0.042		
TP2 inspection - near louvers	90.90	0.15	0.492	0.074		
TP3 inspection - near louvers	91.70	0.15	0.592	0.089		
In between louvers	83.20	0.10	0.084	0.008		
Yale Veracitor Forklift with beeper	92.90	0.15	0.780	0.117		
Pedestal Grinder	91.90	0.15	0.620	0.093		
Sander	85.20	0.15	0.132	0.020		
16oz shot peen hammer	112.10	0.05	64.872	3.244		
Breaks and other Activities	65.00	11.45	0.001	0.014		
					3.701	91

4.3.6 Statistical Analysis

All calculations and descriptive statistics were completed using IHSTAT (https://www.aiha.org/public-resources/consumer-resources/apps-and-tools-resource-center) an exposure statistics application developed by the American Industrial Hygiene Association (AIHA). IHSTAT is an Excel application capable of calculating exposure statistics with the use of lognormal (or normal) parametric statistics. Simple linear regression analysis was conducted using Stata version 15 (StataCorp LP) to compare full-shift and task-based methods of exposure assessment.

4.4 Results

The mean dB(A) from the full-shift TWA measurements was below the occupational exposure limit (OEL) for all job roles (Table 7). However, the maximum level was above the OEL for all job roles except the communications technician.

Table 7 Descriptive statistics from personal noise dosimetry results

Job Role	*Number of samples taken (n)*	*Geometric Standard Deviation (GSD)*	*Mean*		*Maximum*		*Minimum*	
			% dose	*dB(A)*	*% dose*	*dB(A)*	*% dose*	*dB(A)*
Fuel Delivery Driver	39	3.279	60.723	82.84	444.3	91.46	3	69.82
Communications Technician	35	3.863	12.03	75.83	55.5	82.45	0.3	59.84
Electrician	50	3.331	41.18	81.16	243.7	88.86	1.8	67.60
Plumber	50	3.128	41.42	81.19	267.3	89.26	0.4	61.10
Power Station Operator	50	3.535	26.43	79.24	150	86.75	0.2	58.10

The simple linear regression analysis indicated excellent agreement between the task-based and full-shift measurements (Figures 6-10) with R^2 values above 0.85 for all job roles. For all job roles, the simple linear regression analysis calculated a coefficient of determination of 0.91 for the agreement of full-shift and task-based measurements showing a good fit for the model against the data (Figure 11). The fit to the data is of the form $dB(A)_D = M * dB(A)_T + C$. A summary of fits and R^2 values is given in Table 8.

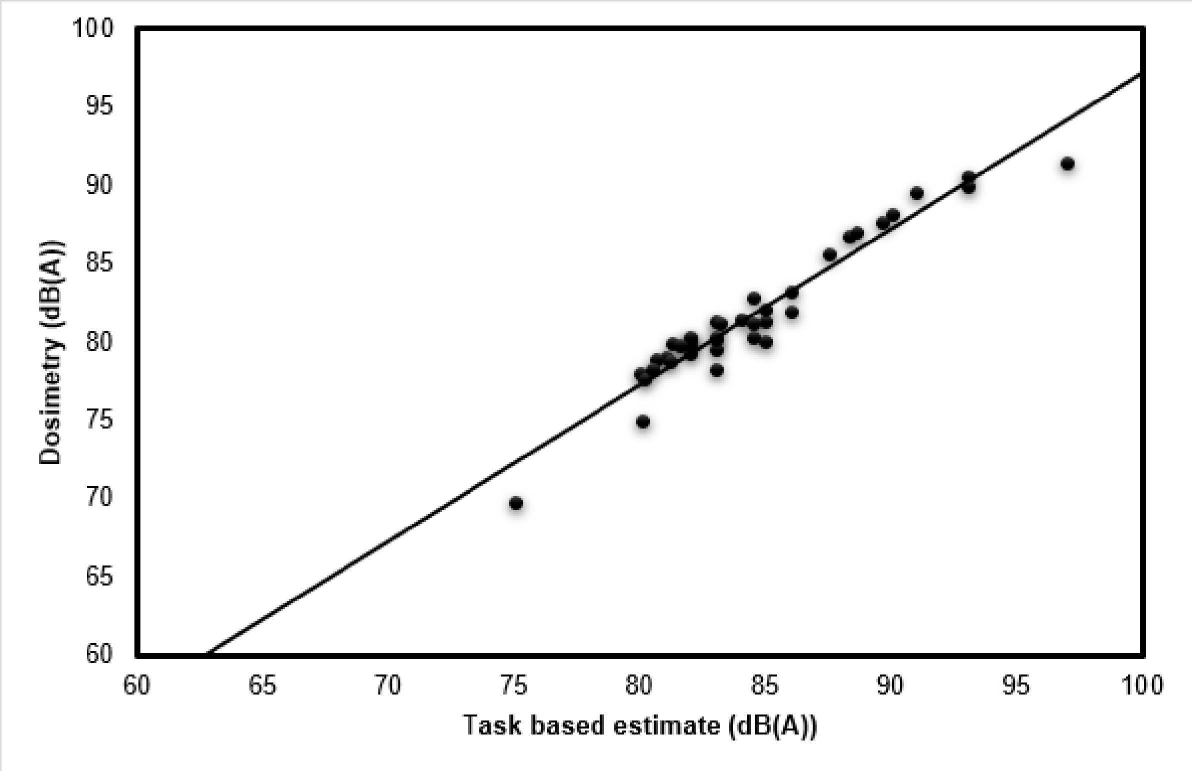

Figure 6 Comparisons of full-shift noise dosimetry with task-based estimates using area measurements for job role Fuel Delivery Driver

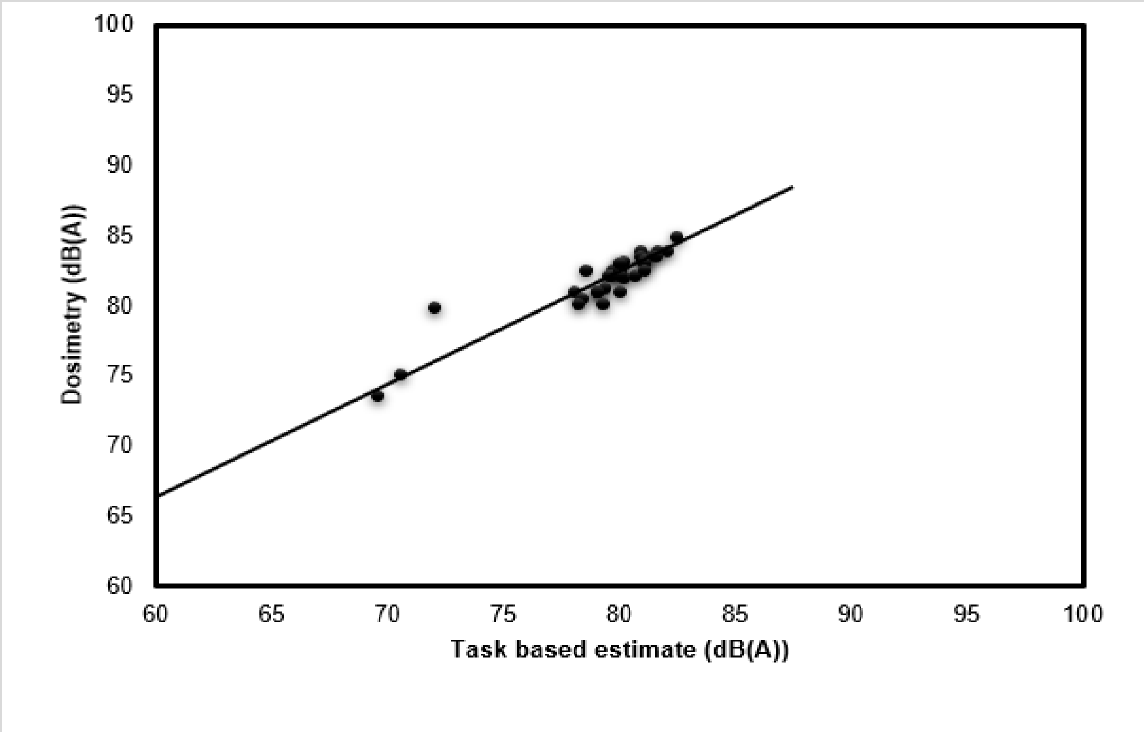

Figure 7 Comparisons of full-shift noise dosimetry with task-based estimates using area measurements for job role Communications Technician

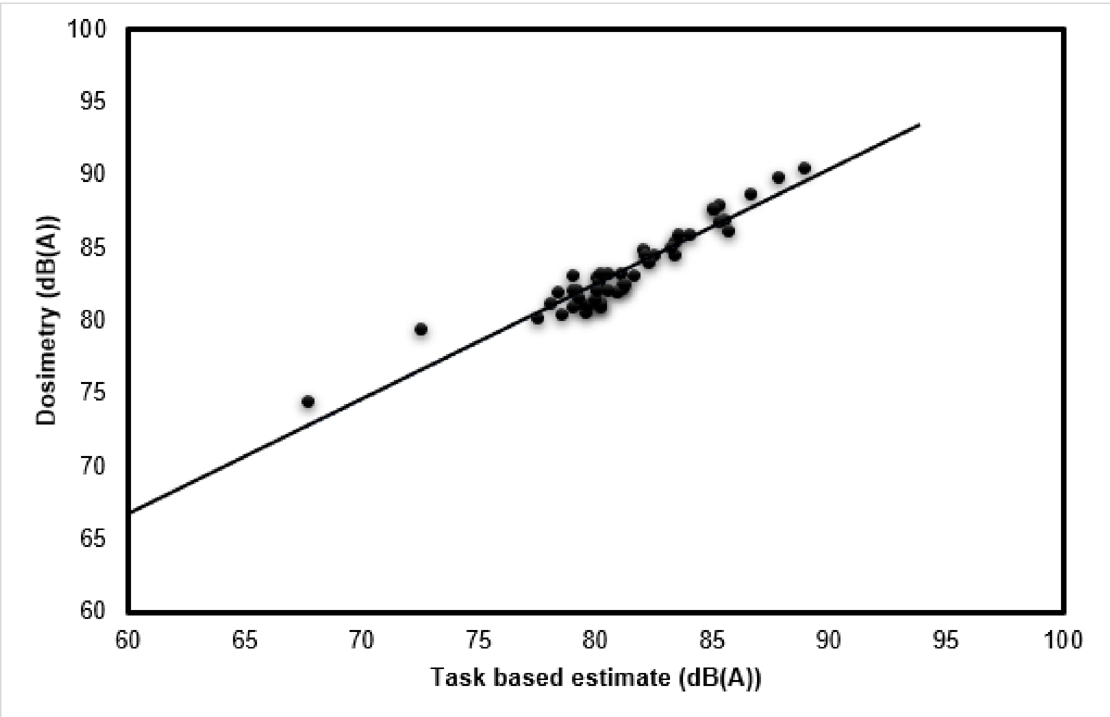

Figure 8 Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for job role Electrician

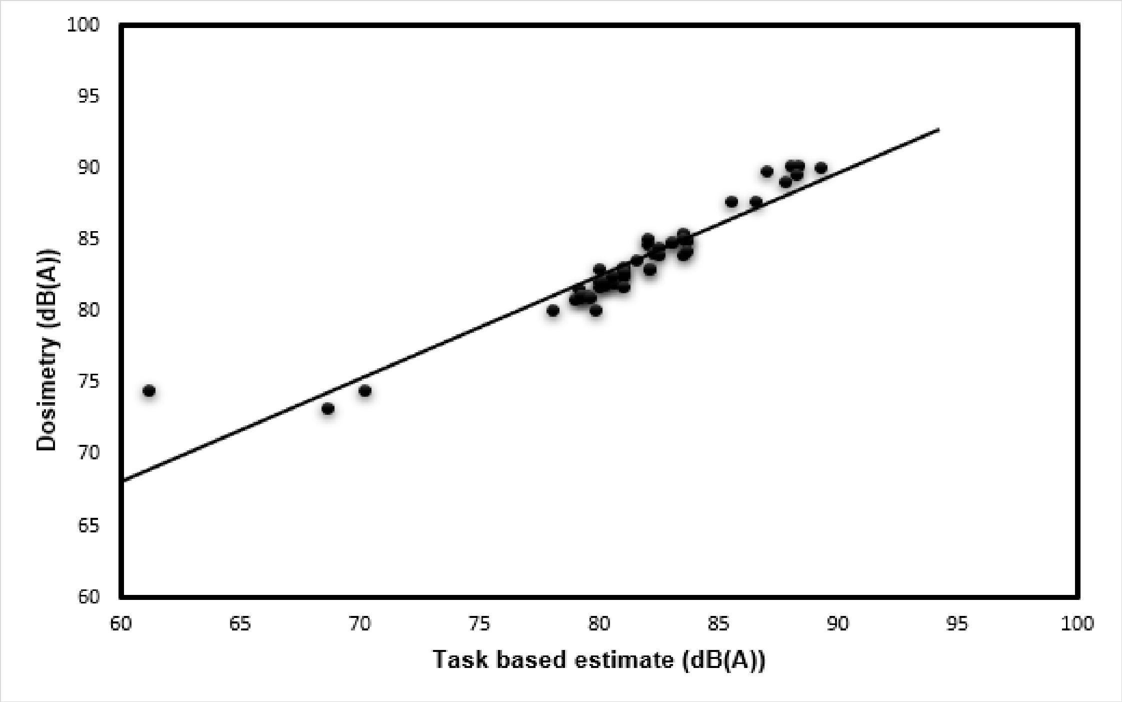

Figure 9 Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for job role Plumber

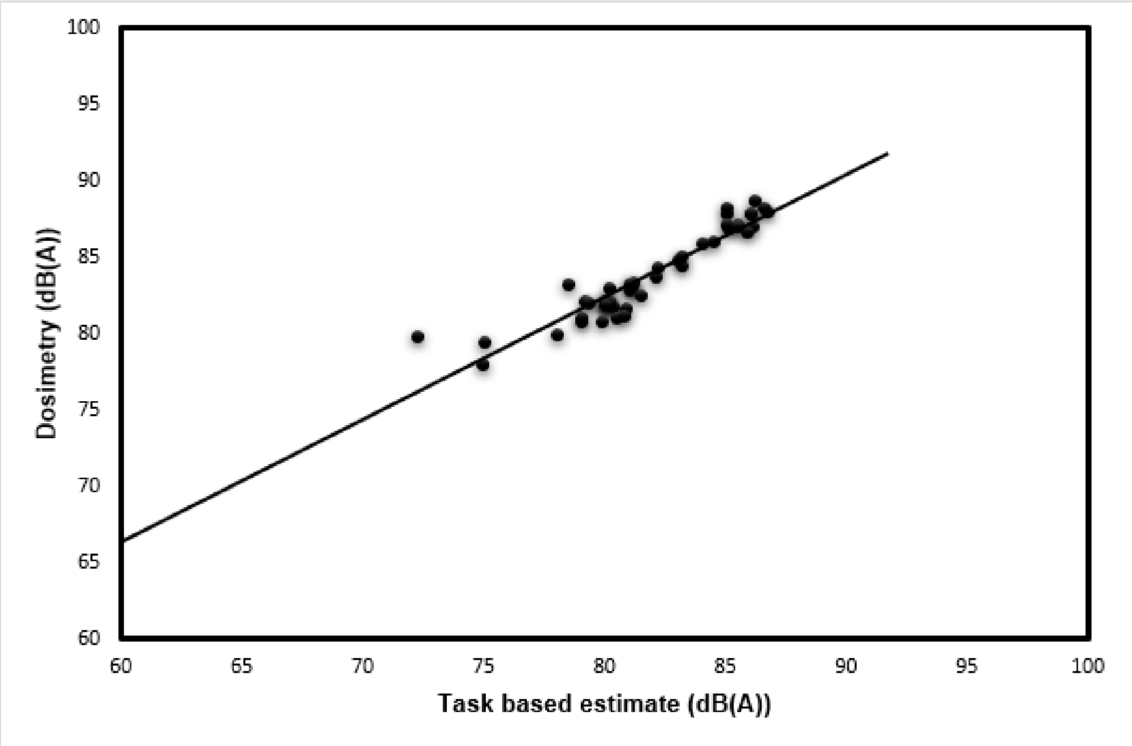

Figure 10 Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for job role Power Station Operator

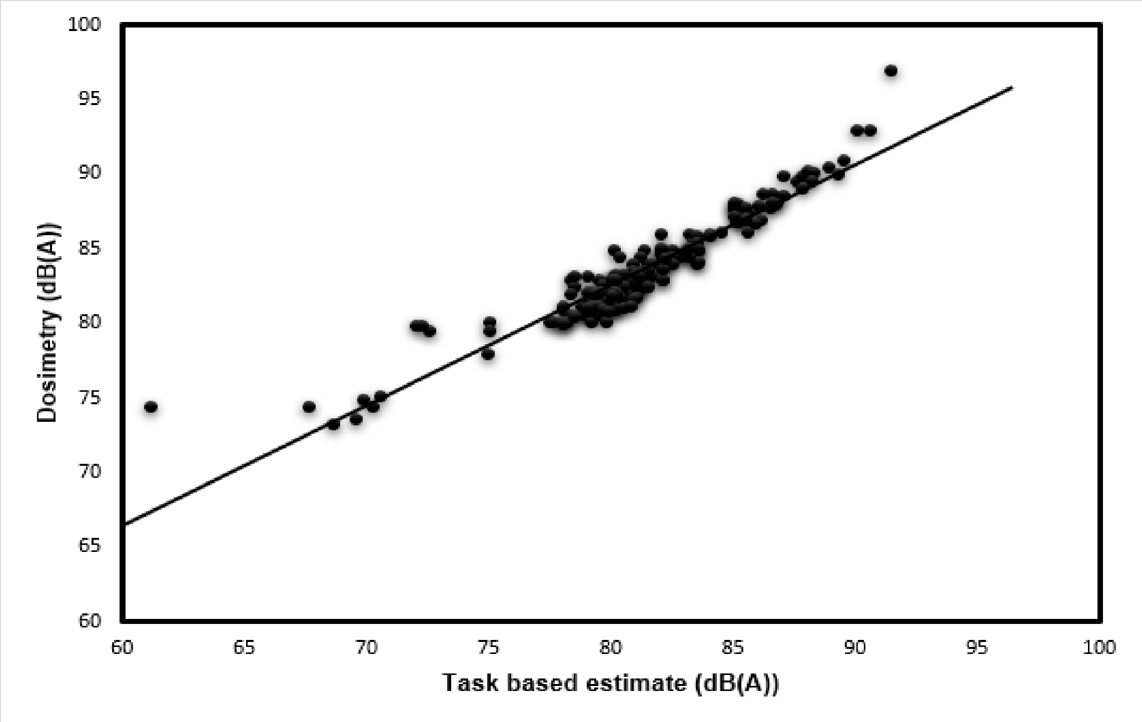

Figure 11 Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for all job roles

Table 8 Summary of simple linear regression fits and R2 values by job role

Job Role Dataset	M	C	R^2
Fuel Delivery Driver	0.996	2.334	0.932
Communications Technician	0.803	18.184	0.935
Electrician	0.788	19.466	0.888
Plumber	0.719	24.884	0.885
Power Station Operator	0.800	18.416	0.936
Combined Dataset	0.806	18.049	0.911

4.5 Discussion

The current study aimed to investigate exposure to occupational noise as experienced by utility workers using a combination of area noise measurements and task activity diaries to reasonably estimate full-shift dosimeter measurements. The results of this study indicate that task-based estimates of noise exposure can be useful in forecasting full-shift noise exposure, when calculated using specific tasks undertaken by job role. The coefficients of determination for all five job roles indicated agreement between full-shift dosimeter measurements and estimates made using area measurements. Considering the variability in the tasks described in the task activity diaries, the task-based estimates are likely to fall within the expected range, providing a good estimate for daily noise exposures.

The three studies in the literature comparing full shift and task-based estimates of exposure to noise (183, 195, 198) highlighted that clearly defining beginning and ending times for each task increases the agreement between estimated and measured daily noise exposures, and there is generally agreement between time-at-task information collected from direct observation and worker self-reports. In general, these studies found moderate to good agreement between measured and task-based estimated daily noise exposures. In estimating task-based exposure to noise, the definition of *task* is paramount. A task can be described as an overall activity, whereby a set of sub-tasks may be present, or can be described at the sub-task level in first instance. For the purpose of accuracy, the more specific the description of the task to be measured, the better the precision in assessing the task, and hence the more credible the output data of the task-based measurement taken (183).

The current study demonstrates that, provided a task is defined accurately with the assistance of the operator completing the task, then assessment of these tasks can also be accurate enough to accommodate variability between tasks in a dynamic environment. A worker's input into tasks completed on a day that they were sampled is crucial to understanding the key elements of the worker's shift that may have contributed to exposure values measured. This information is known to be unreliable when collected retrospectively (13), therefore the task activity diaries within this study were completed with each worker directly after their shift to increase task recall accuracy. This appears to be a key point of difference in in the agreement between area and personal measurements within the context of this study (ranging 0.885 – 0.936), compared to other studies (6, 12, 13).

From a practical standpoint, the good correlation demonstrates that the calculation given ($dB(A)_D = M * dB(A)_T + C$) provides an equivalency factor between dosimetry and area measurements for noise. The fitted equations, given the strong agreement between individual job roles and to the whole dataset, suggest that this calculation may work for all occupations and provide a standard agreement between the two methodologies dependent on equipment utilised. The implication for the occupational hygienist is that, providing task characterisation is accurate, TWA exposures have the potential to be accurately characterised utilising a static sampling method, meaning statistically valid representation across multiple members of a work group over a fixed period may not be necessary to estimate noise exposure.

4.6 Conclusion

This work builds upon similar research conducted by Seixas et. al (183) and Virji et al (198) wherein the agreement between task-based estimated and full-shift noise exposures and comparisons between estimated and measured daily noise exposures were assessed respectively. Both studies found that agreement can be observed between task-based and full-shift estimates, however this is largely contingent on factors such as specificity of task definition and worker reports (183, 198). Building upon these determinants, the current study utilised worker input into tasks completed on the day that sampling was completed to increase task recall accuracy, and this appears to be a key factor in in the agreement between area and personal measurements.

Task-based noise exposure analysis has the potential to be widely used in the utilities industry. While full-shift monitoring to determine TWA exposures is useful, the changing work environment, variability in tasks and equipment, and varying workday hours, limit the ability of the 8-hr TWA to accurately characterise the exposures and associated health risks for utility workers. For some utility providers, access to occupational hygiene services may be limited; meaning a complete noise survey conducted to determine personal exposures may not be viable. An alternative noise exposure analysis methodology, developed from a comprehensive task-based exposure database, is thus an attractive option for estimating the personal noise exposures of workers with irregular tasks, such as those in the utilities industry.

4.7 Acknowledgements

We would like to thank all the workers who participated in the sampling program.

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Chapter 5: Use of expert elicitation in the field of occupational hygiene: comparison of expert and observed data distributions

As discussed in Chapters 1 and 2, subjective judgements form an important part of the occupational hygiene profession. Therefore, it is important to understand the quality and validity of these judgements, including how much variability there is between judgements. This chapter presents the findings of a study wherein we assess the professional judgement accuracy of a group of occupational hygienists when completing exposure assessments on a range of airborne contaminants across several job roles within a surface mining environment. Subjective expert judgements are compared directly against the equivalent measured data in order to measure accuracy.

The following manuscript was submitted on 22 November 2021 and accepted for publication on 25 May 2022. This chapter presents the accepted version of the following article:

Lowry DM, Fritschi L, Mullins BJ, O'Leary RA. Use of expert elicitation in the field of occupational hygiene: Comparison of expert and observed data distributions. PloS one. 2022 Jun 8;17(6): DOI: [10.1371/journal.pone.0269704](https://doi.org/10.1371/journal.pone.0269704)

It has been published in the final form at:
https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0269704

A copy of the published manuscript can be found in Appendix H.

A summary of this paper has been presented at the following conferences:

- British Occupational Hygiene Society (BOHS) OH2022 – Sustainable Workplace Health Conference held in Belfast from 20 to 23 June 2022
- 38th Annual Conference and Exhibition of the Australian Institute of Occupational Hygienists (AIOH) held in Sydney from 19 to 23 March 2022
- 33rd International Congress on Occupational Health 2022 (ICOH 2022) Conference held virtually in Melbourne and Rome from 6 to 10 February 2022

A copy of the relevant excerpts from individual conference proceedings can be found in Appendices L – N.

5.1 Abstract

Introduction: The concept of professional judgement underpins the way in which an occupational hygienist assesses an exposure problem. Despite the importance placed on professional judgement in the discipline, a method of assessment to characterise accuracy has not been available. In this paper, we assess the professional judgement of four occupational hygienists ('experts') when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment in the Pilbara region of Western Australia.

Methods: The job roles assessed were project driller, mobile equipment operator, fixed plant maintainer, and drill and blast operator. The contaminants of interest were respirable crystalline silica, respirable dust, and inhalable dust. The novel approach of eliciting exposure estimates focusing on contaminant concentration and attribution of an exposure standard estimate was used.

Results: The majority of the elicited values were highly skewed; therefore, a scaled Beta distribution was fitted. These elicited fitted distributions were then compared to measured data distributions, the results of which had been collected as part of an occupational hygiene program assessing full-shift exposures to the same contaminants and job roles assessed by the experts.

Conclusion: Our findings suggest that the participating experts within this study tended to overestimate exposures. In addition, the participating experts were more accurate at estimating percentage of an exposure standard than contaminant concentration. We demonstrate that this elicitation approach and the encoding methodology contained within can be applied to assess accuracy of exposure judgements which will impact on worker protection and occupational health outcomes.

5.2 Introduction

Accurate exposure judgments are the foundation of efficient and effective exposure management. The principal goal of the occupational hygiene professional is to protect all workers by reducing workplace health risks to as low as reasonably practicable. Of paramount importance is understanding worker exposure through direct measurement, but limited resources usually mean that hygienists need to apply a level of 'professional judgement', that is, the determination of whether an occupational exposure is acceptable based on limited information (22). Qualitative exposure judgments based on subjective professional judgement form the foundation upon which most exposure assessments are based, and their accuracy is essential in ensuring appropriate risk management outcomes (23, 54, 201). Professional judgement is considered a tool in the toolkit of the hygienist alongside the series of statistical parameters and analyses (i.e., sample size calculation, result aggregation, conformance assessment based on decision statistics) that are useful for describing exposure profiles in a quantitative fashion. However, the circumstances under which professional judgement is prescribed and understanding who can adequately dispense this expertise is still a topic for which ambiguity exists. Although the notion of professional judgement is generally accepted in the discipline of occupational hygiene, the definition is open to interpretation. Professional judgement may be exhibited through the application of knowledge, skills and experience in a way that is informed by professional standards, laws and ethical principles to develop an opinion or decision.

Any strategy where occupational hygienists make exposure judgments without adequate information or data has the potential to introduce inaccuracy and bias which could leave workers unprotected (22). The process of making exposure judgments with inadequate information has sometimes been referred to as the 'art' of professional judgment. Expert elicitation is the process of retrieving and quantifying expert knowledge in a particular domain (202). The use of expert elicitation helps to introduce a structure for validation to make the process more transparent and effective (22, 23, 54).

5.2.1 Accuracy of professional judgement

The application of professional judgement is an integral part of a hygienist's role and can determine whether resources applied to risk controls, respiratory protection, health surveillance and awareness programs effectively protect workers. Several studies have been published on the accuracy of professional judgment when completing exposure assessments in the field of occupational hygiene (136-138, 140-142). Some (23, 24, 54) involved a desktop assessment where qualitative task information and quantitative sampling data were provided while others relied on a walkthrough assessment where direct task observation was employed. The quantitative studies demonstrated that the accuracy of exposure judgments made by hygienists when monitoring data are available is low (<50% correct judgments) but still better than chance (25%) (23, 24). A number of factors relating to experience, training, certification, and educational level were significant predictors of judgment accuracy (23, 24). Findings from the walkthrough assessment approach where monitoring data were not available indicated the accuracy of exposure judgments made by hygienists (30% correct judgements) was not much different from chance (25%) (23, 24) and underestimation bias was also present.

Most exposure judgments made by hygienists are qualitative and can often be the determining factor as to whether any measurements should be made. Low accuracy of these judgments can therefore lead to incorrect follow-up activities, which may place workers at risk. Recent findings suggest that the understanding of how workplace factors affect exposure needs to be significantly improved among practitioners (138, 148) and that low accuracy in exposure assessment could be due to occupational hygienists receiving little formal training on how to conduct a basic exposure characterisation (149). If this step of the exposure assessment is not conducted in a systematic way the hygienist may not investigate the exposure that presents the highest exposure potential with enough detail, leading to low judgment accuracy (149).

5.2.2 Cognitive biases and heuristics

A principal factor relating to the accuracy of professional judgement may be that of cognitive biases associated with the understanding of skewed lognormal distributions which are common in industrial hygiene data (23). (19). When reviewing these distributions, mental shortcuts, known as heuristics, are often used which can lead to errors in judgment and introduce bias., There are three types of heuristics: availability, representativeness, and anchoring and adjustment (116, 117). The availability heuristic reflects the tendency to equate the probability of an event with the ease with which an occurrence can be retrieved from our memory (116, 117). For example, a hygienist may recall a family member or acquaintance who has suffered an asbestos-related disease, and thus may judge severity of asbestos exposure on the experiences of those around them. This may lead to a discounting of offsetting information, especially when such data conflict with easily recalled personal experience (118). The degree to which a person's experiences and memory matches the true frequency determines whether these judgments are accurate. The representativeness heuristic reflects the assignment of an object or event to a specific group or class of events. If the decision maker lacks relevant experience, a surrogate (and less relevant) memory may be used, such as using a normal distribution rather than a skewed log-normal distribution. The anchoring and adjustment heuristic is a strategy for estimating uncertain quantities (116, 117). When trying to determine the correct value, our minds 'anchor' on a value, and then adjust to accommodate additional information. The degree to which our final answer is anchored to the initial value can be influenced by many factors resulting in incorrect conclusions.

Despite these drawbacks, the use of expert knowledge in decision making has been gaining traction (152-154). and has been shown to improve decision making across a broad range of disciplines, including psychology (115, 136), drug delivery and development (155), transdermal delivery and toxicity (156) environmental exposure assessment (157), habitats of rare species (158) and aggregate exposure assessment (159). These approaches are particularly useful in areas where a traditional approach of using measured data may be problematic, such as occupational exposure assessment.

The main purpose of this study was to use expert elicitation to assess the professional judgement of a group of occupational hygienists (‘experts’) when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment. To achieve this, we assessed professional judgment accuracy by comparing expert judgements with quantitative exposure monitoring data.

5.3 Methods

An expert is commonly defined as someone with comprehensive and authoritative knowledge in an area not possessed by most people (150). In the discipline of occupational hygiene in Australia, practitioners who attain the status of Certified Occupational Hygienist (COH) are recognised as experts in their field, and this was a prerequisite for participation in our study. The expert group consisted of four COHs, who all had working knowledge of the mining industry (currently employed in mining industry with a minimum of 15 years’ experience working in a mining environment), the job roles, the contaminants of interest and the units and scales to be used in the elicitation process (203). Notification of recruitment for the study was distributed through email with four of ten experts self-selecting into the study. Informed consent was obtained prior to participation. Two of the participating experts were located in Perth, Western Australia and two experts were located in Brisbane, Queensland. All four experts held a bachelor’s degree, with three of the experts holding a master’s degree and one holding a doctorate. All participating experts were male with the age range being 35 – 56 years. All data analysis was conducted by the authors in Perth, Western Australia.

5.3.1 Expert elicitation framework

One of the most important aspects of an elicitation protocol is the choice of summary statistics used to describe the distribution and the order in which these statistics are elicited (160-162). These summary statistics need to be meaningful to the experts, especially when the experts have limited statistical and probability knowledge (113).

We created a protocol for elicitation which had the experts estimating point estimate values in the following sequence (i) lowest expected value (lowest value that would not surprise the expert), (ii) highest expected value (highest value that would not surprise the expert), and (iii) most common expected value (estimated most likely value that would lie between estimated 'lowest' and 'highest' values). The exact wording "most common" was employed to make certain that the elicited parameter matched to the model (mode of the distribution). The experts were asked to estimate both concentration and percentage of relevant occupational exposure limit (OEL). The elicitation steps, parameter descriptors, elicitation tool (Excel document) and relevant exposure limits were provided to the experts by email (refer to elicitation tool in the supplementary data). The elicitation tool and instructions given to the experts are provided in Appendix K.

5.3.2 Measured data

The measured data were collected in the form of full-shift, personal samples for the following job roles - project driller, mobile equipment operator, fixed plant maintainer, and drill and blast operator (Table 9). Locations for sampling included six iron ore mines located in the Pilbara region of Western Australia. The contaminants of interest were respirable crystalline silica, respirable dust, and inhalable dust. Personal samples were collected and analysed as per the applicable Australian Standard for each agent of interest, these being AS 2985-2009: *Workplace atmospheres – Method for sampling and gravimetric determination of respirable dust* and AS 3640-2009: *Workplace atmospheres – Method for sampling and gravimetric determination of inhalable dust*. Workers were selected randomly whenever possible using a random number table generated through the use of the RAND function in Excel. Equipment used to conduct the air sampling included an SKC AirChek 2000 pump with flexible tubing to 25mm diameter filters supported by a PVC cyclone or IOM sample head, depending on the agent to be measured. The designated flow rate for all samples collected was as per Australian Standards AS 2985:2009 (respirable fractions) and AS 3640:2009 (inhalable fractions) and was adjusted accurately using a calibrated flow meter (Defender 520 Model). All efforts were made to ensure calibration equipment and technique was of such accuracy that the flow rate was measured to within ±5%. Any samples that did not meet flow rate parameters were considered void and not used within the context of this study. Quantitative analysis of all air contaminant samples took place at MPL Laboratories (Perth, Western Australia), an environmental chemistry laboratory accredited for chemical testing with the National Association of Testing Authorities (NATA). Airborne samples for dust were analysed according to AS 2985:2009 for Respirable Dust and AS 3640:2009 for Inhalable Dust, which report the difference between the initial and final weight of the sample filter. Respirable crystalline silica was measured after ashing, redeposition and Fourier-transform infrared spectroscopy (FTIR) determination. Point estimate values of (i) lowest, (ii) highest, and (iii) most common (mode) were calculated from the data set in order to define the true nature of the respective exposure profiles.

Table 9 Personal samples (measured data) collected by contaminant for each job role

Contaminant	**Job role**			
	Project driller	Mobile equipment operator	Fixed plant maintainer	Drill and blast operator
Respirable crystalline silica	*n = 220*	*n = 310*	*n = 200*	*n = 210*
Respirable dust	*n = 220*	*n = 310*	*n = 200*	*n = 210*
Inhalable dust	*n = 300*	*n = 350*	*n = 330*	*n = 280*

5.3.3 Statistical encoding of elicitations

The majority of the elicited values were strongly left or right skewed, e.g., the most common value was equal to the minimum or maximum elicited value. A previous study showed that the scaled Beta distribution provided a better fit than the normal and lognormal distributions, particularly for strongly skewed data (160). Therefore, for each expert, a scaled Beta distribution was fitted to each job role and contaminant combination by scaling the elicited values to the range [0, 1] (160). A least squares approach was used to estimate the α and β parameters of the Beta distribution by ensuring that the distance between the elicited and encoded quantities was minimised using mean sum of squares (MSS) (160, 204, 205). The expert's mode (most common) was defined as $(\alpha - 1)/(\alpha + \beta - 2)$. When the expert's lowest and most common estimate values were the same, then α was set to one and least squares was applied to identify β parameter (160). Similarly, when the highest and most common estimate values were the same, then β was set to one and α was estimated using least squares. The function 'optim' in R (206) was employed to search across the parameter space to identify the best α and β parameters that minimise MSS (207). To estimate a single distribution which captures the combined experts' values, we applied linear pooling by calculating the sum of the individual expert's distributions (154, 160).

The measured data were also encoded into scaled Beta distributions. The mode and the lower and upper bounds for the 95% confidence interval were calculated for each job role and contaminant measured data combination. These summary statistic values were then encoded into scaled Beta distributions using the same methodology as the elicited values.

5.4 Results

The participating experts reported a timeframe of between 45-60 minutes to complete all elicitations (all job roles, all contaminants), and all experts expressed confidence that the process captured their knowledge of exposure. Figures 12–14 show the individual and combined expert plausible (density) estimates of exposure concentration (mg/m^3) compared with the measured data across the four job roles with respect to each contaminant and Figures 15-17 show values in percentage of the relevant OEL. The term 'plausibility' can be defined as the degree of expert support on the estimates of exposure concentration and OEL estimates (160). Most measured data follow a lognormal distribution, exhibiting right (positive) skewness (208), and this is observed in 60% of the measured data distributions (all Figures except 12 and 15). Within all Figures, the experts are denoted in the colours blue, red, black and green. The combined expert's distribution is denoted with a dashed line and measured data is presented as a purple line.

Comparison of the most common exposure value between the experts and the measured data demonstrate that all experts provided a value higher than the measured value for all contaminants and all job roles, meaning exposure has been overestimated for both percentage of the OEL and concentration in all elicitations. For the highest exposure value, the experts overestimated exposure 41% and 54% of the time respectively for OEL and concentration. For the lowest exposure values experts overestimated exposure 96% of the time for both OEL and concentration when compared with the measured data.

For inhalable dust concentration, all four experts were similar to the measured data distributions for the job roles of fixed plant maintainer and mobile equipment operator (Figure 12). However, for the other two roles, the green expert estimated higher values than the other experts and the measured data.

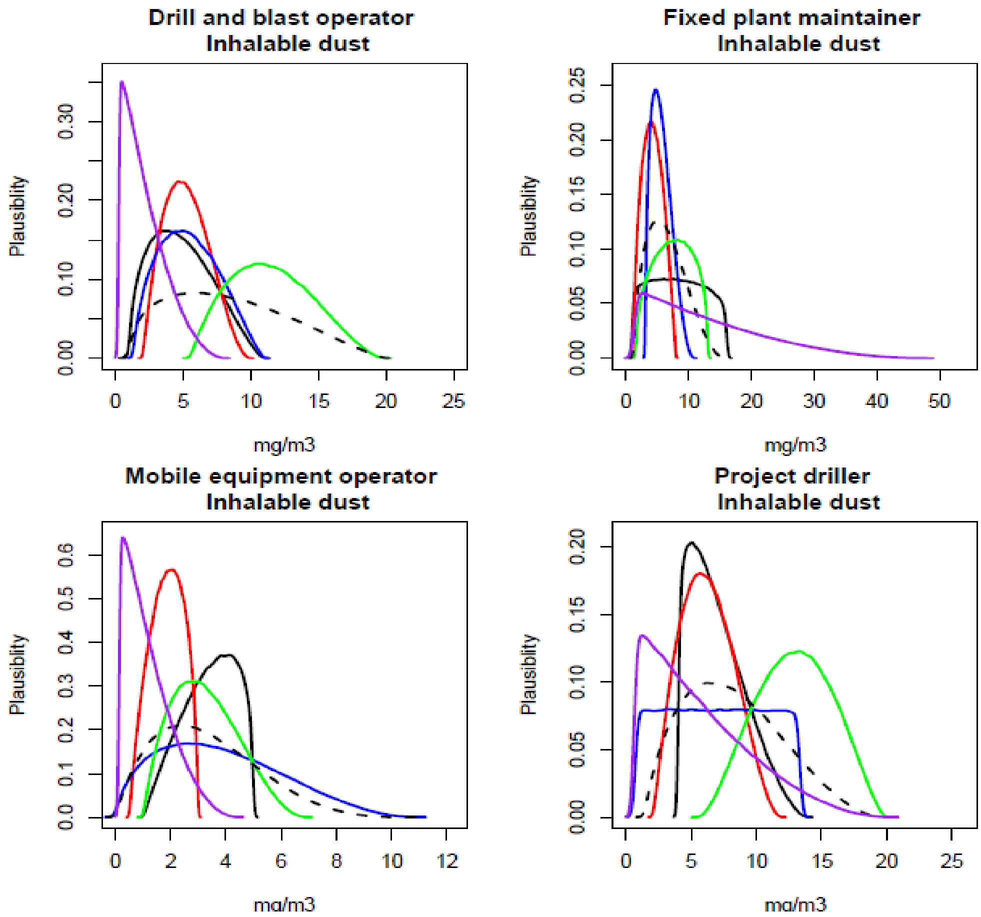

Figure 12 Expert estimates and measured data of inhalable dust concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

Figure footnote: Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

For all four respirable crystalline silica plots, the measured data had very tight distributions (Figure 13). The blue expert's distribution was very wide compared to measured data and all other experts' distributions. For the job role drill and blast operator, all experts' most common values were higher than the measured distribution. For fixed plant maintainer, the blue expert was lower and most common values agreed with the measured data; however, the other three (black, red and green) expert's lower and most common values were higher than the measured data.

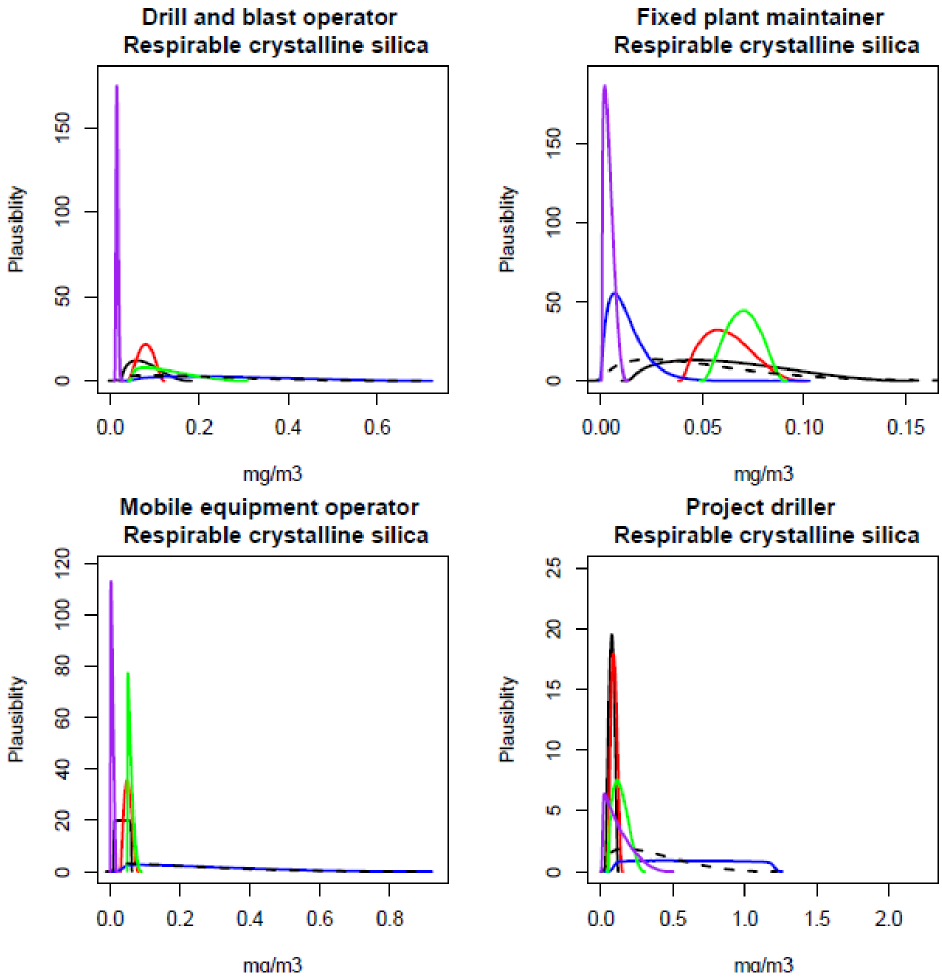

Figure 13 Expert estimates and measured data of respirable crystalline silica concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

For respirable dust concentration, no expert agreed with the measured data, and the range of blue and green experts' distribution was similar (Figure 14). The green expert's distribution was very different to the measured data and all other experts' distributions for the job role project driller.

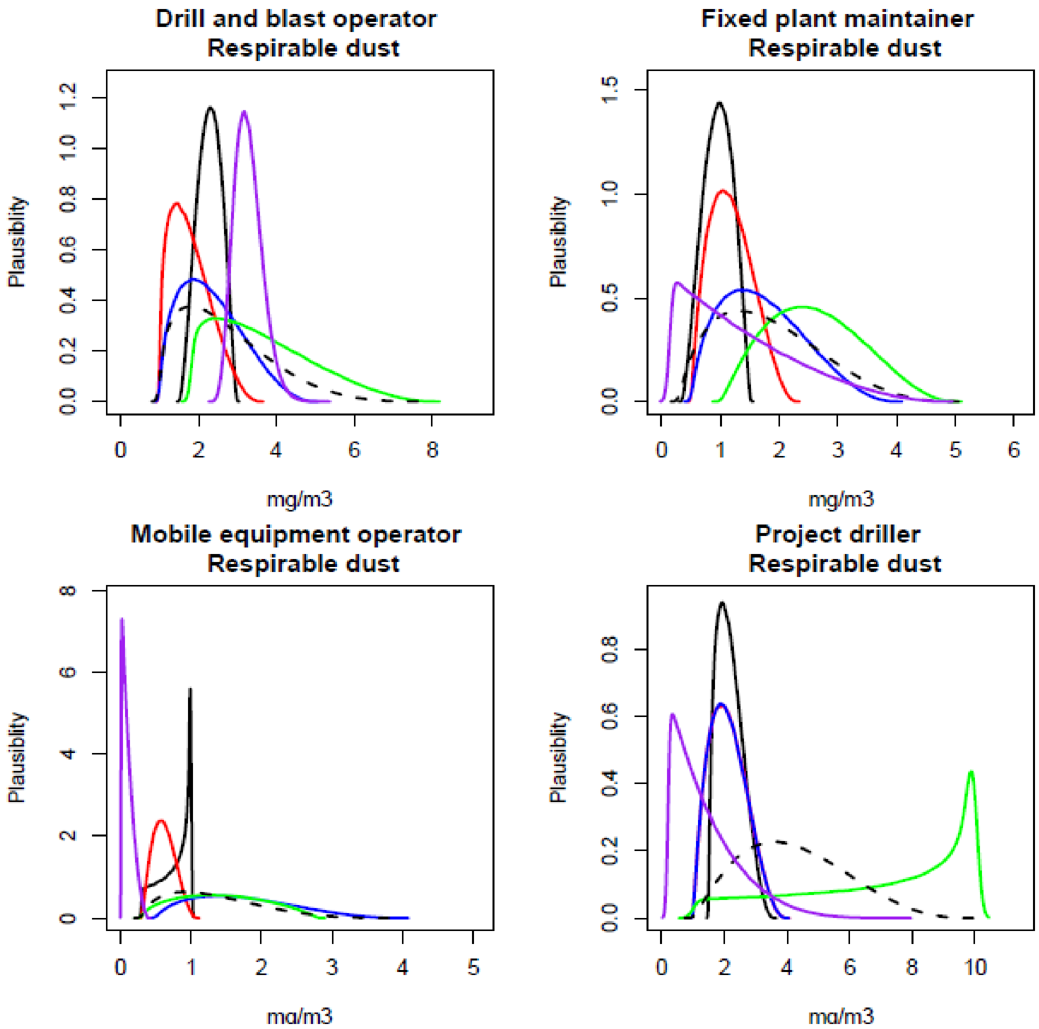

Figure 14 Expert estimates and measured data of respirable dust concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

For the estimates of the percent of the inhalable dust OEL, all expert distributions fell within the range of the measured data (Figure 15). In addition, all expert distributions were similar to the measured data for the job role of fixed plant maintainer. For the other job roles, the modes (most common value) of the expert distributions were higher than the measured data. All estimates of the most common value were similar to the measured data for the job role of project driller when assessing the percent of the OEL for respirable crystalline silica (Figure 16). For the other three job roles, the blue expert distribution had a wide range when compared to the measured data and other experts.

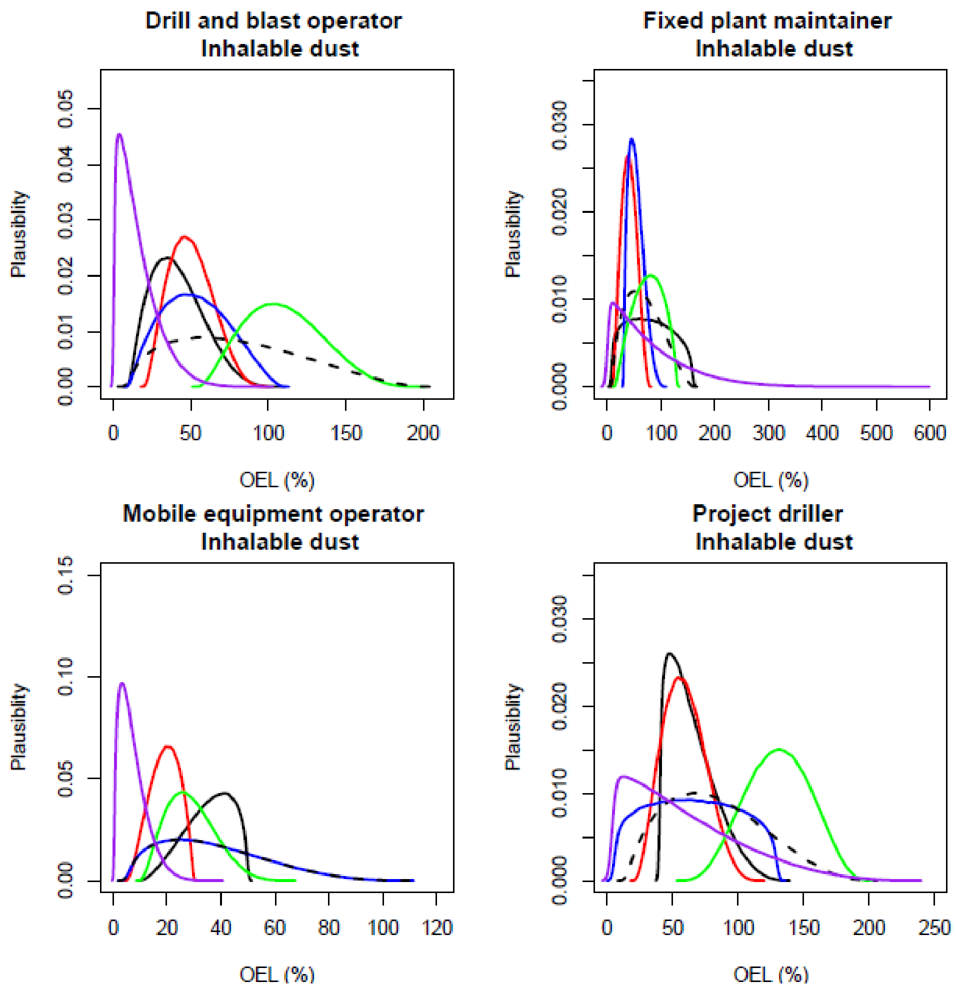

Figure 15 Expert estimates and measured data of inhalable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

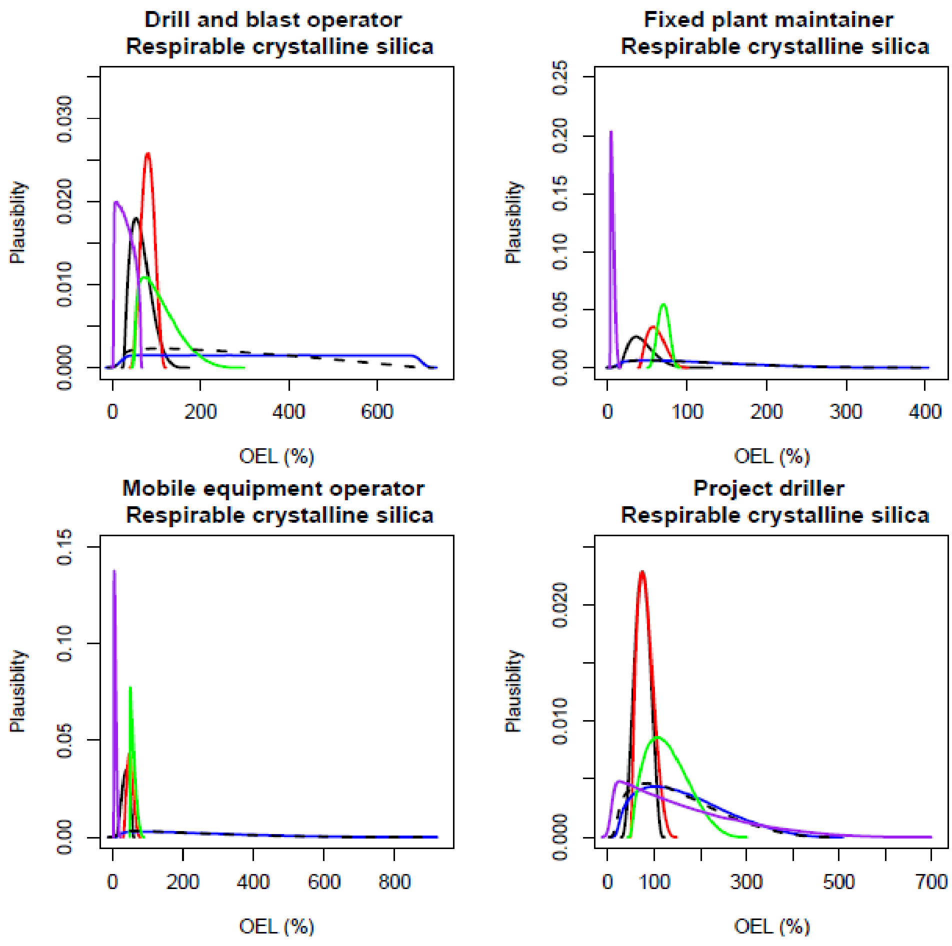

Figure 16 Expert estimates and measured data of respirable crystalline silica percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

For the assessment of the percent of the respirable dust OEL, the measured data distribution were right skewed except for the job role of mobile equipment operator (Figure 17). The green expert's distributions disagreed with the measured data in all four job roles. All lowest elicited values were in the range of the measured data. For drill and blast operator, all experts had a similar distribution compared with the measured distribution, however the most common value of all the experts was slightly higher compared to the mode of the measured data. Descriptive statistics for the measured data are provided in Appendix J.

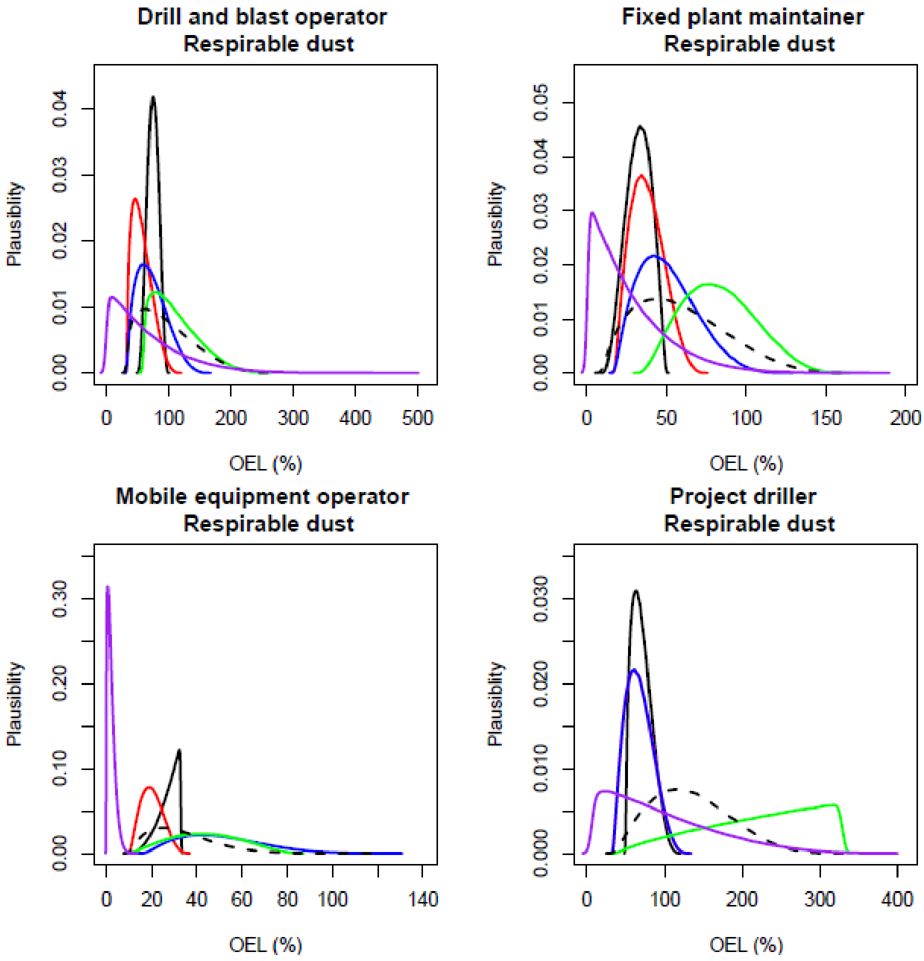

Figure 17 Expert estimates and measured data of respirable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

5.5 Discussion

The main purpose of this study was to use expert elicitation to assess the professional judgement of a group of occupational hygienists. We have presented and evaluated a statistical methodology for the encoding of elicited information into distributions from multiple experts. We applied a scaled Beta distribution to expert and measured data; this approach was able to accommodate both left and right skewed distributions as well as “normal” distributions. Our findings suggest that the participating occupational hygienists within this study were inclined to overestimate exposures and that they were more accurate at estimating percentage of OEL than concentration values (refer to study comparison tables in the supplementary data). Our approach differs from previous research in the way in which exposure assumptions were elicited, by focusing on contaminant concentration and attribution of an exposure standard percentage estimate.

The use of expert knowledge in decision making has been gaining traction in many scientific disciplines, most notably in areas where a traditional approach of utilising observed data may not be a practical option (152-154). Most assessments conducted within a comprehensive exposure assessment program are qualitative, that is, completed without measured data. This approach is by design and is practically necessary, as the number of exposure scenarios in a workplace may total in the hundreds in which conducting quantitative exposure assessments (i.e., using measured data with sufficient samples to support decision making) for every scenario is not feasible (201). For example, the American Industrial Hygiene Association (AIHA) exposure assessment strategy calls for initial, qualitative assessments of exposures, relative to a reference exposure level (19).

Occupational hygienists review the workforce, materials, exposure agents, tasks, equipment, exposure controls and identify exposure groups that will be assessed and controlled depending on the final judgments. The exposure evaluation for any job role requires the selection of an OEL and a judgment by the hygienist about where the decision statistic (for example, the 95th percentile of the exposure distribution for the job role) falls in relation to the OEL (19). Professional judgement is considered a 'tool in the toolkit' of the hygienist and serves as a key factor when making a determination on whether an exposure is acceptable in the context of an occupational environment. However, for the most part, subjective qualitative judgments in the field of occupational hygiene have proven to be no more accurate than random chance. This may be because patterns of exposures in many workplaces have a significant degree of uncertainty and unpredictability and there may be little or no data available on these exposure levels. Such situations have been defined as 'low-validity' environments (115) and perhaps somewhat paradoxically, judgement decisions have been shown to be most accurate in these highly uncertain situations, particularly when paired with checklists or models. The use of a checklist that considers consistent inputs is shown to be more reliable at arriving at a judgement than a purely 'human' focussed way but this has not previously been assessed in the occupational hygiene setting (115). (24, 54).

A key observation from this study is the experts' proclivity to consistently overestimate exposures. This appears to be a point of difference when compared to similar studies where there was a significant underestimation bias in the exposure judgments when the range is examined (23, 24, 54). The reasons behind this finding are worth exploring. In other expert elicitation studies (152-154) experts are typically able to estimate the range of measured data distribution quite accurately, however the most common value tends to be higher than the measured value. Our study found that the most common exposure value between the experts and the measured data was higher than the measured value for all contaminants and all job roles for both percentage of the OEL and concentration in all elicitations. We found that the experts lowest exposure value was nearly always (96% of the time) higher than that of the measured equivalent and the highest exposure value was overestimated about half of the time (41% and 54% of the time for percentage of OEL and concentration respectively). These findings suggest that hygienists may be more concerned about the upper bound of an exposure profile as opposed to the lower and therefore concentrated more on estimating this more carefully.

Comparing the expert versus the measured data distributions show that the experts appear to be able to estimate percentage of the OEL more accurately than concentration. This may be attributable to a variety of factors, including risk communication. Given one of the mandates of the occupational hygienist is to 'distil' complex data into easy-to-understand messages for a workforce, many hygienists have taken to expressing results of monitoring data as percentages of the applicable exposure standard and so this way to present data is likely to be more familiar to them.

With respect to the experts, the green expert was notably divergent from the measured data and their elicitations often yielded different results from the other experts. This disparity warrants further investigation into how the green expert executed the elicitations, and whether any cognitive biases attributable to the heuristics of availability, representativeness, and anchoring and adjustment were present during this exercise. A deeper dive into the determinants of the elicited values would provide transparency around the decision-making practices of each expert.

A strength of the study was the statistical encoding of both expert and measured data into scaled Beta distributions. The advantage of the scaled Beta distribution when compared with the normal and lognormal distributions is that it performs better over all levels of skewness, in particular providing accurate encoded values under extreme skewness (160). This is particularly useful when the skewness is expected to be high, or in situations where the degree of uncertainty is high. Both situations are present within the context of this study, and this illustrates why probabilistic methods are attractive to hygienists who are required to make exposure judgments with limited sampling data (91).

A further strength of this study was that we had a large amount of measured data to use for comparison against the expert elicitations. A standard approach to exposure assessment in the field of occupational hygiene dictates randomly sampling 6 - 10 events of a specific job role and calculating an upper tail decision statistic such as the 95th percentile with an upper confidence limit (e.g. 90th or 95th) (19). This approach to exposure assessment has been utilised in the field for many years and was based on the assumption of a stable and predictable work environment wherein a reliable mean and geometric standard deviation can be calculated after 6 – 10 samples (19). With the advent of a more dynamic workforce expected to complete multiple tasks across different work environments (as is the case in the mining industry), the concept of full-shift personal monitoring to define the exposure profile of a job role or similar exposure group (SEG) may not be an optimal approach. Given this, the large dataset in this study was useful in capturing the real distribution of the measured data that may be present in a dynamic work environment (209). With the introduction of sensor measurement technology (sometimes referred to as ‘real-time’ monitoring) future studies may focus on comparisons between experts and quantitative measurements that are task or source based, which may present a more accurate picture of a worker’s exposure in a dynamic occupational environment.

A potential limitation of this study was the number of experts recruited for elicitation. Although there is no absolute guideline on which to base the number of experts invited to provide input, a panel of expert elicitation practitioners determined that at least six experts should be included to ensure robustness of results (210). The same panel also concluded that a point of diminishing returns was reached beyond twelve experts. Future studies may wish to expand the number of experts involved to further broaden the range of experiences that contribute to a person's professional judgement. However, a challenge to these further studies is the availability of both general and industry-specific experts. In addition, the study was completed in the context of a mining environment with only three agents of interest, all of which were particulates. Future studies should ensure a larger sample size of experts are recruited and assessment be focused to a larger suite of airborne contaminants across other industries.

Another limitation of the study are the uncontrolled conditions that the expert elicitations were completed. The elicitation steps, parameter descriptors, elicitation tool (Excel document) and relevant exposure limits were provided to the experts by email; however, the authors were not aware, and did not specifically enquire, as to any additional resources or information used by the experts when completing their judgements. In addition, a 'hard' timeframe for return of the elicitation tool with completed judgements was not set by the authors, rather a 'request' was made to return the completed protocol document within a two-week period. Further studies should ensure that any additional resources or information utilised during the elicitation process are categorised and reported. Given the role of a practicing hygienist, it may be impractical to expect elicitations be completed under controlled conditions (i.e., in a supervised exam room), however specifying a set timeframe for completion of the elicitation protocol should also be considered.

5.6 Conclusions

The results in this study suggest that, in the absence of measured data and under the same methodology described within this paper, the participating occupational hygienists tended toward an overestimation of exposures. The practical implication of overestimating may be an 'overprotection' of workgroups, or a misallocation of resources such as risk controls, respiratory protection, health surveillance and awareness programs. Conversely, the consequences of underestimating exposure (as has been reported in other studies) may leave workers unprotected.

From a practitioner standpoint, hygienists would err toward a more conservative approach to protecting worker health if given the choice; however, there are pros and cons to this. For example, a conservative approach may result in higher order respiratory protection being prescribed in the absence of actual risk, which may impact adversely on an individual's metabolic load. In a high heat environment, the result of this could be dangerous to the individual through the development of a heat-related illness. Similarly, overestimation may result in scant resources not being adequately apportioned based on risk, which could extend out to critical health surveillance (i.e., disease identification) services.

Despite these findings, it is clear that the field of occupational hygiene is integral to the global effort of protecting worker health. The elicitation protocol used in this study, although reflective of 'real world' challenges of assessing exposures in the absence of measured data, was designed to require a high degree of specificity when the experts were making their respective judgements. The concept of exposure assessment is complex, with the amount of information required to be assessed often exceeding the capacity of the pre-frontal cortex, the decision-making area of the brain (201, 211). This overload can make the brain vulnerable to flaws of memory and distraction, which can lead to bias and over-confidence in decision-making (201, 211).

These findings suggest that improved accuracy in exposure assessment in the absence of measured data is needed, particularly in the context of a dynamic work environment where job roles are expected to complete tasks across different work fronts, as is the case within an Australian mining context. Further efforts should assess the expert's decision-making process and the determinants of their judgements. Future research should focus on these determinants of professional judgement to better assess accuracy and inform formalised training programmes, models, and other tools to improve exposure assessment within the discipline of occupational hygiene.

5.7 Acknowledgements

We thank the occupational hygienists who participated in this study by contributing their expert judgements.

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Chapter 6: Assessing accuracy of occupational noise exposure estimation using expert elicitation

In the previous chapter, we described a study wherein we asked occupational hygienists to submit subjective expert judgements for a range of airborne contaminants and compared these directly against the equivalent measured data to measure accuracy. This chapter presents the findings of a study wherein we assess judgement accuracy within a group of occupational hygienists when completing exposure assessments for occupational noise across several job roles within an open-cut mining environment. We chose to separate this study from the previous study detailed in Chapter 5 on account of the complexities associated with interpreting logarithmic scales as discussed in Chapter 2.

The study outlined in this chapter has been submitted for publication and is currently under review.

Lowry D.M., Fritschi L., Mullins B.J., O'Leary R.A. (2022). Assessing accuracy of occupational noise exposure estimation using expert elicitation. *Manuscript submitted for publication.*

6.1 Abstract

Introduction: Exposure to occupational noise constitutes a significant health risk in the occupational environment. The issue of noise exposure is well known within the discipline of occupational hygiene and is present in many industries worldwide. In this paper, we assess professional judgment accuracy amongst occupational hygienists when subjectively assessing exposures to occupational noise across four job roles in a mining environment.

Methods: The approach of eliciting exposure judgements focusing on noise dose and percentage of the relevant exposure standard was used. The elicited values were then compared to the equivalent measured data using a scaled Beta distribution.

Results: The participating hygienists underestimated the range at both ends of the exposure distribution. Comparison of the most common exposure value between the experts and the measured data showed that the experts provided a value lower than the measured value 56% of the time, meaning exposure has been underestimated for both percentage of the OEL and concentration in just over half of all elicitations. Individually, all but one expert underestimated exposure 50% of the time. For the highest exposure value, the experts underestimated exposure 100% of the time for both OEL and concentration. For the lowest exposure values, the experts overestimated exposure 100% of the time for both OEL and concentration when compared with the measured data.

Conclusions: Findings suggest that overestimation of exposure values can occur when hygienists are completing subjective exposure assessments using decibel dose. In addition, hygienists may underestimate exposures when completing subjective assessments using percent of occupational exposure limit. We conclude that the logarithmic scale used to measure decibels impacted negatively on judgement accuracy for the participating hygienists.

6.2 Introduction

Exposure to noise constitutes a significant health risk in the occupational environment. There is sufficient evidence indicating excessive and prolonged noise exposure can induce hearing impairment, hypertension and ischemic heart disease, sleep disturbance and general annoyance (178). The issue of noise exposure is well known within the discipline of occupational hygiene and is considered a ubiquitous and invasive contaminant present in many industries worldwide. Recent studies indicate that 22 million U.S. workers are exposed currently to high noise levels on-the-job and 25% of U.S. workers have a history of occupational noise exposure at some point in their careers (212, 213). Although global estimates are scarce, the prevalence of noise exposure at work (i.e., the percent or number of all cases at a given time) has been reported to be approximately 15% in Canada (214), 20% in the European Union (215), and 20% in Australia (216).

Noise is defined by intensity (measured in decibels or dB) and frequency (measured in cycles per second and expressed as hertz or Hz) (217). The decibel is a dimensionless unit of pressure and is logarithmic – each doubling of pressure yields an increase in 6 dB in sound pressure level (SPL) (21). The primary risk to human hearing is thought to begin with long-term (i.e. 40 year work life) exposure to sounds approaching or exceeding 85 dB (21, 217).

Effective management of noise and hearing loss prevention in the occupational environment starts with a thorough understanding of noise sources and exposures. For occupational hygienists, this will often take the form of a walkthrough survey to quantify basic noise hazards and to identify predominant emission sources and worker interaction with these sources (21, 29). For quantitative measurement, occupational hygienists are trained to take a similar approach as they would to assessing airborne contaminants, that is through the identification of SEGs and the planning of a baseline sampling campaign, the results of which can be compared to a regulatory limit to assess compliance (21). However, most exposure assessments made by occupational hygienists are undertaken with minimal or no monitoring data at all due to resourcing, time, or other constraints (24). As discussed in Chapters 1 and 2, in the absence of sufficient data, occupational hygienists interpret the available workplace information using their professional judgment and make decisions regarding appropriate controls (24, 54). Therefore, there is a heavy reliance on the accuracy of professional judgments and the ability of occupational hygienists to correctly integrate them with monitoring data to make accurate exposure decisions (20). Subjective exposure judgement may be particularly challenging for a hygienist given occupational noise varies widely in its characteristics, such as sound level, spectral content, intermittency, and impulsiveness (217) and this may present as a barrier to accuracy. In addition, accurate exposure judgements of occupational noise may be difficult in industries like mining and construction, which feature large temporal and spatial exposure variability (218).

Perceived noise exposure intensity and duration have been assessed via self-report in several epidemiological studies (219-223). Whenever self-reported information is used, recall bias is a consideration; however, self-reported data on exposure durations and work environments (224, 225) and on specific work activities (225) may be accurate enough for use in exposure assessment. Previous studies have demonstrated that workers' subjective perceptions of the intensity of their occupational noise exposures correlated well with brief sound level measurements (219) and that survey items relating to perceived exposure intensity exposure could be used to identify workers with full-shift levels over 85 dB (221). Neitzel et al. (218) assessed noise exposure using workers' subjective perceptions of their own exposure levels. The results of the study suggested that subjective exposure assessment has the potential to be used as a sensitive and specific screening tool to identify overexposed workers for compliance purposes (218). However, no studies appear to have evaluated the accuracy of subjective exposure assessment of noise amongst occupational hygienists.

The main purpose of this study was to use an expert elicitation tool to assess judgement accuracy in a group of occupational hygienists when estimating noise exposure across several job roles within an open-cut mining environment.

6.3 Methods

Methods undertaken in this study were previously described in Chapter 5 and the elicitation tool and instructions given to the experts are provided in Appendix P. Differences in approach are provided below.

Personal noise samples were collected and analysed as per AS/NZS 1269-2005 (199) and workers were selected randomly whenever possible using a random number table generated using the RAND function in Excel. Equipment used to conduct noise sampling consisted of personal noise dosimeters (type 4448, Brüel and Kjær, Nærum, Denmark) calibrated pre and post sampling with a sound calibrator (type 4231, Brüel and Kjær, Nærum, Denmark). A total of 415 dosimeter measurements were captured across the four job roles (Table 10).

Table 10 Personal noise samples (measured data) collected for each job role

Job role			
Project driller	Mobile equipment operator	Fixed plant maintainer	Drill and blast operator
n = 30	*n = 141*	*n = 112*	*n = 132*

6.4 Results

The participating occupational hygienists reported a timeframe of between 45-60 minutes to complete all elicitations. Figure 18 shows the individual and combined expert estimates of exposure concentration in dB(A) compared with the measured data across the four job roles and Figure 19 shows values as percentages of the relevant OEL. Comparison of the most common exposure value between the experts and the measured data show that the experts provided a value lower than the measured value 56% of the time, meaning exposure has been underestimated for both percentage of the OEL and concentration in just over half of all elicitations. Individually, all but one expert underestimated exposure 50% of the time. For the highest exposure value, the experts underestimated exposure 100% of the time for both OEL and concentration. For the lowest exposure values, the experts overestimated exposure 100% of the time for both OEL and concentration when compared with the measured data. Descriptive statistics for the measured data are provided in Appendix O.

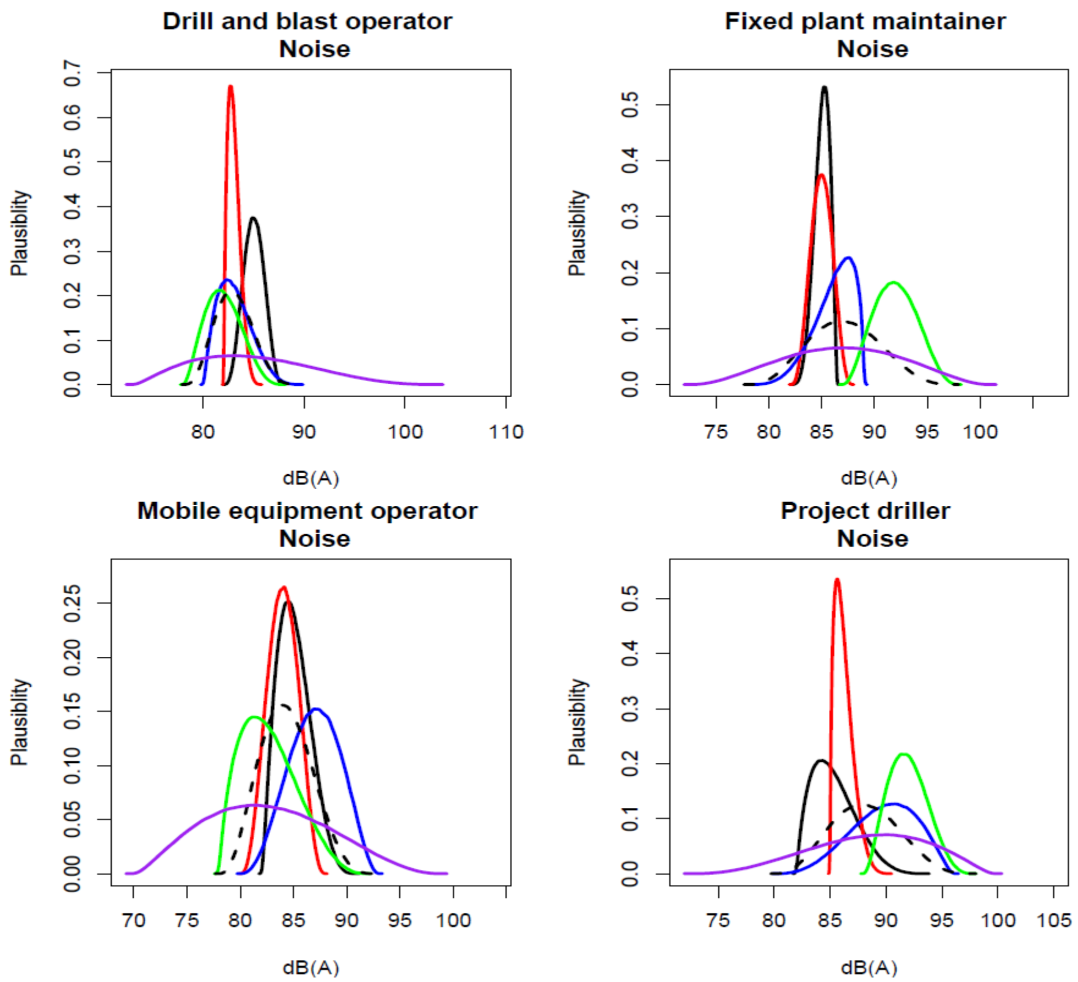

Figure 18 Expert estimates and measured data of noise concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

Figure footnote: Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

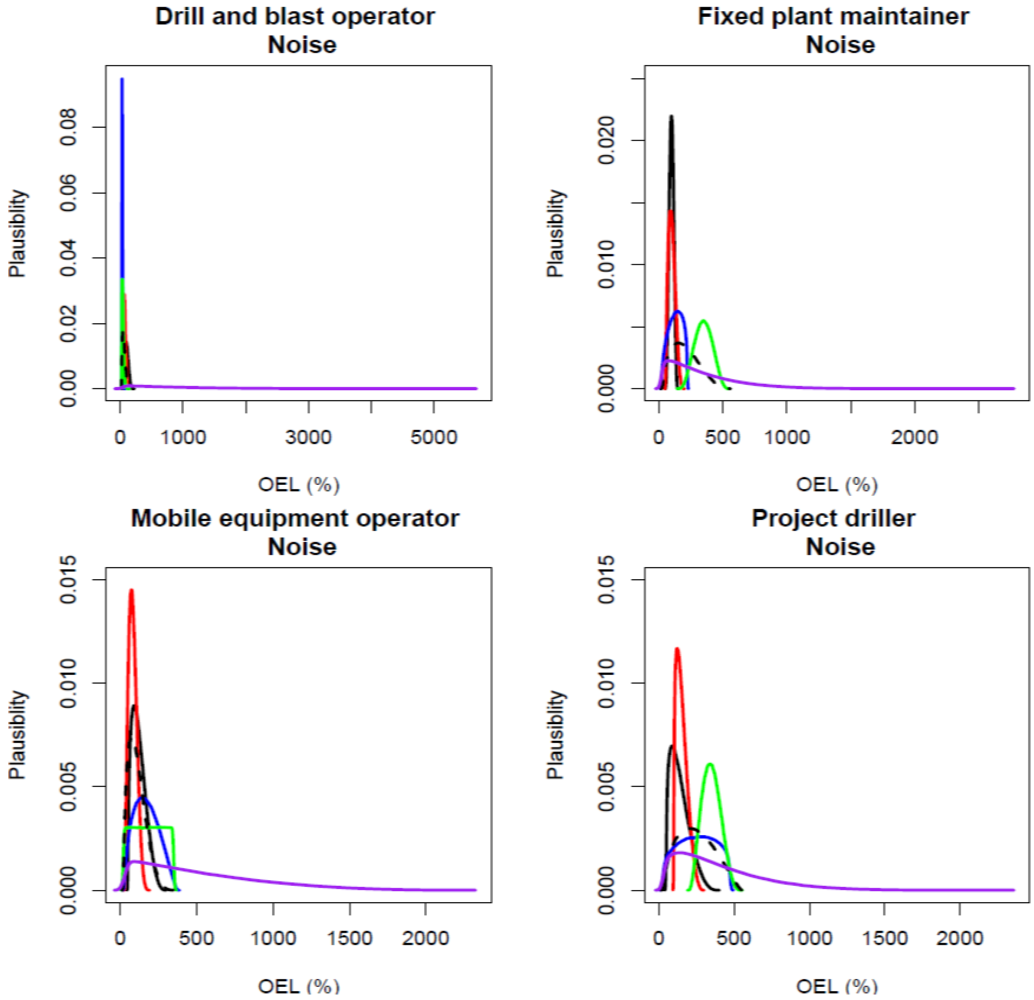

Figure 19 Expert estimates and measured data of noise for percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution

6.5 Discussion

Our findings suggest that the occupational hygienists who participated in this study were inclined to both overestimate and underestimate occupational noise exposure depending on the value being elicited. Specifically, the hygienists tended to underestimate the range for all parameters, and to overestimate the most common exposure value when providing decibel dose estimates (measured on a linear scale) and underestimate exposure when providing percent of relevant exposure standard (measured on a logarithmic scale).

The use of expert knowledge in decision making has been used in many domains of science to great effect (152-154); however, there is minimal literature assessing expert elicitation in the area of occupational noise. In one study, expert-based noise estimates were evaluated by four industry experts who rated 54 sawmill jobs to assess exposure-response relationships between cumulative noise exposure and acute myocardial infarction (AMI) mortality (226). Measurement-based noise estimates were derived from statistical models that accounted for job, mill, and time differences. The model-based estimates were adjusted to account for the use of hearing protective devices (HPD). The correlations between the expert-based and the measurement-based unadjusted and HPD-adjusted cumulative noise estimates were 0.81 and 0.57, respectively (226). The HPD-adjusted model-based estimates provided the most precise exposure-response relationship; no associations were observed with the unadjusted or expert-based noise estimates. Some other studies suggest that occupational noise may be accurately assessed by experts. Ising et al. (219) found that individuals were well able to self-report noise exposure, with a strong correlation (Spearman r = 0.84) between the self-reported exposure categories and noise dosimetry.

Comparison of the most common exposure value between the experts and the measured data show that the experts provided a value lower than the measured value 56.23% of the time, meaning exposure has been underestimated for both percentage of the OEL and concentration in just over half of all elicitations. For the highest exposure value, the experts underestimated exposure 100% of the time for both OEL and concentration. For the lowest exposure values, the experts overestimated exposure 100% of the time for both OEL and concentration when compared with the measured data. These findings suggest that hygienists find it difficult to predict range of exposure, and that an underestimation bias may be present when attempting to predict the mode of the distribution. The underestimation bias seems to agree with similar studies where there was a significant underestimation bias in the exposure judgments when the range was examined (23, 24, 54) although it should be noted that none of these studies included the assessment of occupational noise.

A potential challenge associated with interpreting and contextualising occupational noise is the use of the logarithmic scale, and this can be seen in the results through the experts' overestimation and underestimation biases. As discussed in Chapter 2, logarithmic scales have been demonstrated as difficult to interpret (129, 131, 132), including in practicing scientists who have substantial statistical training and frequently use and encounter logarithms (133).

A potential limitation of this study was the number of experts recruited for elicitation. Given the inclusion criteria for the experts, this was not unexpected. In addition, the study was completed in the context of a mining environment. Future studies should ensure a larger sample size of experts are recruited and assessment be focused across other industries.

6.6 Conclusions

Our findings suggest that the participating hygienists tended to underestimate the range for all parameters, and to overestimate the most common exposure value when providing decibel dose estimates (measured on a linear scale) and underestimate most common exposure when providing percent of relevant exposure standard (measured on a logarithmic scale). We conclude that the logarithmic scale used to measure decibels impacted negatively on judgement accuracy for the participating hygienists. A key implication of underestimating exposure is that this can lead to workers being left unprotected (21). The practical implication of overestimating exposures may be an *overprotection* of workgroups, or a misallocation of resources such as risk controls, hearing protection, health surveillance and awareness programs. These findings suggest that improved accuracy in exposure assessment is needed. On the issue of interpreting the logarithmic scale, we would recommend that any official curriculum underpinning the occupational hygiene profession include guidance on how to interpret log-scaled axes and equations. There are several studies in the literature indicating that misinterpretations of log-scaled data are not caused by practitioner negligence, but rather by deeply held misconceptions (133). Based on this, occupational hygiene educators should not merely remind student hygienists of the correct use and interpretation of logarithms, but directly combat misconceptions by creating cognitive conflict via a method known as ‘refutational teaching’ (227). This method has students analyse why the wrong answer is wrong, rather than why the right answer is right. Research in psychology and science education (227-230) supports refutational teaching as a means of reducing misconceptions and producing conceptual change which may be of relevance in the occupational hygiene field on account of misconceptions about logarithms being so firmly held. Another consideration may lie in the ease with which occupational noise is measured, the portability of the equipment, and the real time feedback afforded by contemporary measuring devices. Given these advantages, it may be less important to improve upon subjective occupational noise judgements, however these considerations should sit with the practitioner to determine.

6.7 Acknowledgements

We thank the occupational hygienists who participated in this study by contributing their expert judgements.

6.8 References

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Chapter 7: General discussion and conclusion

This chapter presents a revisitation of the research aims, and a discussion of the key findings of the thesis and implications for the profession of occupational hygiene. This chapter also briefly discusses the strengths and limitations of the thesis, explores future directions and ends with overall conclusions.

The primary aim of this PhD research project was to examine experience and current practices with respect to exposure assessment processes and judgement amongst occupational hygienists. To do this, three key research questions were addressed:

1. How do occupational hygienists describe their experience and current practices with respect to exposure assessment in professional practice and judgement?

2. For occupational hygienists who cannot follow a standardised approach for exposure assessment due to constraints, what other avenues are available?

3. Accuracy in exposure assessment is important. Sometimes occupational hygienists need to make decisions based on very little (or no) measured data – how good are they at doing this?

7.1 Key findings, strengths, and limitations

In this section, the results of each of the four studies conducted are briefly summarised. Strengths and limitations of the research were addressed in each chapter for the individual studies; however, this section also presents a brief overview of these.

Study 1 (Chapter 3) investigated professional judgement, decision making, and current exposure assessment approaches of occupational hygienists via an online survey that was completed by 189 occupational hygienists worldwide. The results of this study suggest that practice variation in exposure assessment exists amongst occupational hygienists, with the principal findings being that hygienists use different strategies, and that departures from standardised processes are largely driven by practical considerations like budget and site inspection findings. The responding hygienists identified improvement opportunities for exposure assessment across the areas of randomised sampling, basic hazard identification, and task-based exposure monitoring. A key strength of this study is that it provided an avenue from which to hear from hygienists around key areas of practice, providing rich insight into what is working well in the profession, through to improvement opportunities and constraints. A potential limitation of this study was the small number of hygienists recruited for participation, a total of 189 respondents of a total combined membership base of approximately 12,000 people. In addition, a convenience sampling strategy with social media was deployed to collect data, which may have elicited a selection bias.

Study 2 (Chapter 4) compared two methods of exposure assessment to ascertain the utility of task-based over full-shift monitoring. Full shift occupational noise measurements (*n* = 224) for a group of workers were taken and then compared to task-based noise measurements using linear regression analysis. Strong, positive, linear associations were found between full shift and task-based measurements (R^2 values above 0.85 for all job roles). We concluded that task-based exposure assessment has the potential to be used by occupational hygienists, particularly when tasks are well-defined. A potential limitation of this study may be the level of detail collected through the task activity diaries accompanying each personal sampling result. Most companies do not collect task or exposure determinant related detail on a routine basis (231) therefore the repeatability of this study may be a difficult undertaking.

Study 3 (Chapter 5) assessed professional judgment accuracy amongst occupational hygienists for a range of air contaminants (inhalable dust, respirable dust, crystalline silica) across four job roles in a mining environment using expert elicitation. An elicitation protocol was developed, and four occupational hygienists provided their subjective judgements for the air contaminants and job roles. These judgements were then compared to equivalent measured data using a scaled Beta distribution model. We found that an overestimation bias was present for all participating occupational hygienists, and accuracy was higher when estimating percent of an exposure standard than the contaminant concentration.

Similarly, *Study 4 (Chapter 6)* assessed professional judgment accuracy amongst occupational hygienists when subjectively assessing exposures to occupational noise across four job roles in a mining environment using expert elicitation. A similar method to *Study 3* was used. Findings suggest that overestimation of exposure values can occur when hygienists are completing subjective exposure assessments using decibel dose. In addition, hygienists may underestimate exposures when completing subjective assessments using percent of OEL. We concluded that the logarithmic scale used to measure decibels impacted negatively on judgement accuracy for the participating hygienists.

A strength of the professional judgement accuracy studies described in Chapters 5 and 6 was the statistical encoding of both expert and measured data into scaled Beta distributions which allowed direct comparisons to be made between elicited and measured estimates of exposure. A further strength of these two studies was the large amount of measured data used for comparison against the expert elicitations. A key limitation for both studies was the number of hygienists that participated, a total of four practitioners for each study.

In summary, this thesis has made a significant and original contribution to understanding current exposure assessment practices of occupational hygienists. This picture of practice provides insight into where departure from standardised practice is occurring, which presents as an opportunity for future education and training within the profession. In addition, the proven utility of task-based sampling is shown to be useful for practitioners who are not able to follow a standardised exposure assessment approach on account of varying constraints. Finally, the professional judgement accuracy studies highlight areas for practicing hygienists to focus on in order to improve accuracy in subjective exposure assessment.

7.2 Implications

The results within this thesis present several implications for the occupational hygiene profession.

As detailed in Chapters 1 and 2, the profession of occupational hygiene has a long and rich history, the roots of which were seeded by pioneers in the occupational medicine field hundreds of years ago. And yet, despite these historical underpinnings, the profession has not focused inward to identify areas of continuous improvement to the extent that other professions have. A good example of this is the concept of variation in exposure assessment practices between hygienists, an area that has not previously been studied in the field of occupational hygiene. Based on our findings, variation amongst practitioners is evident, but we do not know whether this variation is warranted. Unwanted practice variation in a profession where the goal is to protect an individual's health has the potential to have a devastating effect (232). For hygienists, variation may take the form of a step in a process not being followed, the wrong decision statistics being used, an ineffective control being recommended or implemented, or a misallocation of critical resourcing such as PPE or health surveillance services. Although under-studied in the profession of occupational hygiene, a considerable body of evidence has developed internationally showing significant variation in medical practice (233). Although not entirely analogous, the medical profession provides a good proxy for comparison with occupational hygiene given the shared aims of person-centred practice, evidence-based practice, and professional judgement and decision making. For example, there is evidence of variation in medical practice within Australia, and also between Australia and other OECD countries (234), between clinicians, at the service level (between different health services) and at a geographic level (between regions and countries) (233). This level of introspection has presented the medical profession with opportunities to improve their important line of work through first identifying areas where variation is occurring, and then finding suitable avenues to reduce unwanted variation to practice (for example, using checklists, feedback or supervision) (177, 232, 235-237). To that end, the work in this thesis acts as a first step toward an introspective view of the occupational hygiene profession.

This thesis has also demonstrated the utility of three modalities of enquiry not commonly utilised within the field of occupational hygiene – survey, expert elicitation, and modelling – which can be used to further augment the current view of practice amongst occupational hygienists. A review of the literature yielded only one study featuring a survey targeted to and completed by occupational hygienists, and this was focused on knowledge about skin exposure (238). The survey results contained in Chapter 3 serve as perhaps the first published study focusing on occupational hygienists and their practices. As demonstrated, practitioner feedback may be used to highlight which standardised strategies and tools are working well, and which aren't, presenting professional occupational hygiene associations with opportunities to update these documents based on feedback. Over time, regular surveys may build upon this picture of practice and provide the requisite level of introspection needed to ensure that the profession is well positioned to support the changing work landscape which was detailed in Chapter 1.

The expert elicitation approach outlined and the encoding methodology contained within Chapters 5 and 6 were used to assess accuracy of exposure judgements amongst practicing hygienists; however, these studies highlight the practical reality for many practitioners, which is the need to provide accurate exposure judgments based on little to no quantitative data. The findings suggest that hygienists may find it difficult to predict range of exposure, and that an underestimation bias may be present when attempting to predict the mode of the distribution. The implications of these findings are important because, from a practical standpoint, most exposure assessments made by occupational hygienists are undertaken with minimal or no monitoring data at all due to resource constraints (24). Vadali et al. (20) went further by suggesting that greater than 90% of exposure ratings made by hygienists may be based on professional judgments without any monitoring data. As discussed in Chapters 1 and 2, in the absence of sufficient data, occupational hygienists interpret the available workplace information using their professional judgment and make decisions regarding appropriate controls (24, 54). Therefore, there is a heavy reliance on the accuracy of professional judgments and the ability of occupational hygienists to correctly integrate them with monitoring data to make accurate exposure decisions (20). The need to increase accuracy of subjective exposure judgements within the profession needs to be considered to ensure hygienists remain an integral and trusted part of health risk mitigation activities within a workplace.

To further highlight an important limitation previously discussed, a key challenge in expert elicitation studies is the availability of both general and industry-specific experts (151). For example, in 2022 the AIOH had approximately 1200 members nationally, but only 187 of these were certified occupational hygienists (174). Certainly, these numbers present as a challenge for adequate participation in studies conducted focused on occupational hygienists, not just within the context of this thesis, but more broadly. The challenge of limited numbers of hygienists available to participate notwithstanding, there is also the issue of those willing to participate having the time, interest and motivation to participate. Researchers and professional bodies may need to introduce novel ways to incentivise hygienists to take part in future studies in order to maximise participation (239, 240).

The use of statistical models in occupational hygiene exposure assessment is commonplace for researchers (20), however another key implication for the profession may be how modelling can be best integrated into the everyday work of the practitioner hygienist to improve the quality of exposure decision making. Access, training, and a knowledge of when to use modelling is needed at the practitioner level for this modality to be wholly adopted into everyday hygiene practice. Further, future studies may consider how this can be utilised as a feedback tool to improve subjective judgements conducted by hygienists.

A further implication of this work is the juxtaposition between practitioner guidelines for exposure assessment and what practitioners actually do in the field. For instance, as detailed in Chapter 3, the traditional requirement for randomised sampling held little utility for many respondents on account of the complexities and constraints associated with successfully executing true randomisation. Similarly, the dynamic nature of some workplaces and job roles meant that many of the responding hygienists felt a need to explore concepts more likely to provide useful exposure information, such as real-time and task-based monitoring. Broadly speaking, occupational hygienists work across a diverse range of industrial environments and encounter a broad range of exposure problems. Some hygiene practitioners work within large businesses, and others will act as consultants who often must make exposure decisions based on very little time spent in the working environment of interest. This, alongside other constraints (e.g., resourcing, equipment) may present a significant barrier to exposure assessment using a standardised, full-shift sampling strategy. While full-shift monitoring is useful, the changing work environment, variability in tasks and equipment, and varying workday hours, limit the ability of full-shift sampling to accurately characterise the exposures and associated health risks for workers. Current exposure assessment strategies to verify if worker exposures are controlled below the relevant OEL (as discussed in Chapter 2) dictate that personal exposure sampling is required, which involves a worker wearing a monitor over the duration of a shift. Hygienists must then interpret sampling data across an entire shift rather than at a task-by-task level, which produces a single overall exposure result following analysis. With very little insight into what occurs at the task-by-task level, pinpointing specific causes for high exposure is difficult and means potentially harmful exposures may go unseen. Therefore, the implication for task-based monitoring is twofold; first, it presents the hygienist who is time and resource poor with a means to quantify exposures outside of the standardised, full-shift model of exposure assessment. Second, it may in fact be a more useful categorisation of the exposure in question, and may avoid some of the limitations associated with full-shift, TWA sampling, the most notable example being the single result provided, leaving potential for dangerous, short-term ‘peaks’ in harmful exposure to go unseen (241). Given these advantages, it is a reasonable outcome for hygienists to pursue more streamlined exposure assessment approaches that do not necessarily align with traditional dogma.

A final implication from these results presents as a regulatory challenge to the occupational hygiene profession. In many jurisdictions worldwide, full-shift sampling is a legislated requirement (21, 102, 106, 107) and so the assimilation of task-based monitoring into standardised exposure assessment strategies will require demonstrable efficacy and persistent advocacy by practicing occupational hygienists and researchers to give confidence to regulatory bodies that exposures are being adequately characterised and that task-based monitoring is an improvement on current practices.

7.3 Future directions

There are some clear themes from this PhD research that translate into future opportunities for the occupational hygiene profession.

First, some key implications for the profession revolve around how best to consider the information gleaned from Chapter 3. It is clear that there is variability in exposure assessment practices undertaken by occupational hygienists; however, an important consideration is whether variation observed is good or bad, given that variation can be warranted in some cases (242), for example if the following of a standardised procedure will mean that a worker may sustain an exposure and therefore potential harm, a deviation from process would be encouraged. Our results do not highlight whether the variation observed was warranted, and this should be an area of focus for future research on this topic. Further, the results suggest that the notion of randomised, SEG-based exposure assessment strategies focused on compliance may hold little appeal for practicing hygienists, particularly those who are expected to advise a business or workgroup on exposure risk on a limited timeframe or with little resources (i.e., consultants). A solution may lie in the development of clear, technical guidance for task-based assessment, real-time monitoring and hazard characterisation, and the incorporation of these tools into standardised exposure assessment strategies that will ensure hygienists are able to remain agile and relevant in line with future of work challenges (as outlined in Chapter 1).

Second, one of the stark omissions from hygienist's responses to the questionnaire outlined in Chapter 3 centres around a known critical area for improving expertise and judgement accuracy – feedback (243). Previous research has suggested that assessment-based information should be used both to adjudicate outcomes (i.e. accuracy of judgement) and to generate meaningful feedback in order to shape future performance (244). To illustrate this point, consider a theoretical presupposition that decision-making environments vary between two extremes – 'kind' and 'wicked' (245). Kind environments provide feedback that is timely, accurate, and direct. Common examples include board games and sports, which promote a positive learning curve, even for the uninformed decision-maker, because they offer instructive feedback on what should be done next. By repeatedly taking action, people can reliably learn about the environment’s conditions and adapt to them. In contrast, wicked environments are based upon unclear variables, which can be subject to changes across time. As a result, any feedback in this environment can be volatile and often accompanied with a time delay. Wicked environments, such as the stock market or social media, can promote misconceptions about one’s environment and mislead the participant toward wrong judgements and decisions (246-248). Given the dynamic nature of occupational hygiene practice, and the need for hygienists to make decisions under uncertainty, the profession can be best described in the wicked sense of this conceptual framework. Previous studies have assessed the utility of real-time monitoring (241) and Bayesian hierarchical frameworks (93) as a tool for feedback that hygienists can leverage to further refine their professional judgement acumen. In light of this, it is recommended that hygienists look for opportunities, such as real-time monitoring, to target corrective procedures in order to shift their working environments from wicked to kind to improve practice and probabilistic judgements (249). Mentoring and coaching can also assist in helping hygienists at all levels embrace feedback and continue to increase their professional judgement (250).

Third, another opportunity for hygienists resides in the revision and updating of standardised practices to reflect the changing landscape of work. Currently, formalised guidelines for exposure assessment are updated infrequently or in some cases not at all. Examples include the AIHA strategy which has undergone four revisions since its initial inception in 1991, the latest in 2015 (21), and in contrast the NIOSH manual which has not been reviewed or updated since its initial publication in 1977 (98). Given the importance of the profession, its core ethos of protecting worker health, and its integral contribution to regulatory compliance, the lack of progress and continuous improvement in this area is surprising at best and concerning at worst. This thesis has presented the profession with some ideas on how best this opportunity can be capitalised, for example through the use of survey and expert elicitation to provide voice to practitioners. Workplaces today are very complex, and hygienists are not only expected to manage health risk, but also regulatory risk, legal risk, and risks related to the anxiety inherently associated with many people’s emotive response to exposures (21). Occupational hygiene strategies and programs require regular updating of curriculum and research portfolios to stay current and responsive to the needs of the workplace, as well as to remain competitive for increasingly restricted funding (51). With the introduction of sensor measurement technology (241, 251, 252) (sometimes referred to as ‘real-time’ monitoring) future studies may focus on comparisons between experts and quantitative measurements that are task or source based, which may present a more accurate picture of a worker’s exposure in a dynamic occupational environment.

Finally, it is recommended that a community of practice be established for hygienists to work on a consolidated approach to exposure assessment to reflect the changing landscape of work, considering the insights from this thesis. Representation from multiple countries is recommended, with a view of creating a blueprint that may be adapted to accommodate for local legislation (for example, provision of real time monitoring that sits adjunct to full-shift compliance monitoring). University curriculums and professional development programs for hygienists should also endeavour to integrate this information to satisfy the changing needs of the practicing occupational hygienist.

7.4 Overall conclusions

Occupational hygienists have an essential role to play in exposure assessment which directly informs risk mitigation activities and quite literally saves lives (253).

This thesis represents an important addition to the scientific literature, contributing to the understanding of current practices amongst occupational hygienists, decision making, accuracy of professional judgements, and variation from standard work practices. The information obtained from this research can be beneficial in formulating policies, and in improving training curriculums and education and awareness programs for occupational hygienists. In addition, the comparison of two types of exposure assessment methods to assess exposure to occupational noise has contributed to understanding the drawbacks and advantages of these methods and highlighted the importance of the development of exposure assessment methods that are more appropriate for the changing nature of occupational hygiene at large.

As discussed throughout this thesis, the responsibilities of the practicing occupational hygienist are diversifying, with recent challenges and opportunities presenting from the COVID-19 pandemic (46, 47) in addition to technological advancements influencing change in the way our societies live and work (27, 43). The concept of ESG strategies are encouraging the corporate sector to act responsibly beyond seeking profits and disclose related policies and actions (45). With this, there is a realisation that healthy workplaces are essential for global development and progress, and occupational hygienists, with their expertise in anticipating, recognising, evaluating and controlling workplace hazards, will play an important part in this effort (45, 57). Given this, the need for robust practices, accurate decision making, and credibility is essential for the profession to maintain in relevance and grow in stature, and this work is a first step in identifying a baseline from which the profession can progress this effort.

8 References

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9 Appendices

Appendix A: Approval from the Human Research Ethics Office, Curtin University

Curtin University

Research Office at Curtin

GPO Box U1987
Perth Western Australia 6845

Telephone +61 8 9266 7863
Facsimile +61 8 9266 3793
Web research.curtin.edu.au

31-Mar-2021

Name: Lin Fritschi
Department/School: School of Public Health
Email: Lin.Fritschi@curtin.edu.au

Dear Lin Fritschi

RE: Ethics Office approval
Approval number: HRE2021-0156

Thank you for submitting your application to the Human Research Ethics Office for the project **Occupational hygiene decision making: experience, training and education determinants.**.

Your application was reviewed through the Curtin University Negligible risk review process.

The review outcome is: **Approved**.

Your proposal meets the requirements described in the National Health and Medical Research Council's (NHMRC) *National Statement on Ethical Conduct in Human Research (2007)*.

Approval is granted for a period of one year from **31-Mar-2021** to **30-Mar-2022**. Continuation of approval will be granted on an annual basis following submission of an annual report.

Personnel authorised to work on this project:

Name	Role
Fritschi, Lin	CI
Lowry, David	Student

Approved documents:

Document

Standard conditions of approval

1. Research must be conducted according to the approved proposal
2. Report in a timely manner anything that might warrant review of ethical approval of the project including:
    - proposed changes to the approved proposal or conduct of the study
    - unanticipated problems that might affect continued ethical acceptability of the project
    - major deviations from the approved proposal and/or regulatory guidelines
    - serious adverse events
3. Amendments to the proposal must be approved by the Human Research Ethics Office before they are implemented (except where an amendment is undertaken to eliminate an immediate risk to participants)
4. An annual progress report must be submitted to the Human Research Ethics Office on or before the anniversary of approval and a completion

report submitted on completion of the project

5. Personnel working on this project must be adequately qualified by education, training and experience for their role, or supervised
6. Personnel must disclose any actual or potential conflicts of interest, including any financial or other interest or affiliation, that bears on this project
7. Changes to personnel working on this project must be reported to the Human Research Ethics Office
8. Data and primary materials must be retained and stored in accordance with the Western Australian University Sector Disposal Authority (WAUSDA) and the Curtin University Research Data and Primary Materials policy
9. Where practicable, results of the research should be made available to the research participants in a timely and clear manner
10. Unless prohibited by contractual obligations, results of the research should be disseminated in a manner that will allow public scrutiny; the Human Research Ethics Office must be informed of any constraints on publication
11. Approval is dependent upon ongoing compliance of the research with the Australian Code for the Responsible Conduct of Research, the National Statement on Ethical Conduct in Human Research, applicable legal requirements, and with Curtin University policies, procedures and governance requirements
12. The Human Research Ethics Office may conduct audits on a portion of approved projects.

Special Conditions of Approval

It is the responsibility of the Chief Investigator to ensure that any activity undertaken under this project adheres to the latest available advice from the Government or the University regarding COVID-19.

This letter constitutes low risk/negligible risk approval only. This project may not proceed until you have met all of the Curtin University research governance requirements.

Should you have any queries regarding consideration of your project, please contact the Ethics Support Officer for your faculty or the Ethics Office at hrec@curtin.edu.au or on 9266 2784.

Yours sincerely

Amy Bowater
Ethics, Team Lead

Appendix B: Co-author approval for inclusion of papers in thesis

From: Lin Fritschi <lin.fritschi@curtin.edu.au>
Sent: Wednesday, 19 October 2022 9:25 PM
To: Lowry, David (RTIO) <David.Lowry@riotinto.com>
Subject: [External] Permission to include papers

"I give David Lowry permission to include the papers that I have co-authored in his PhD thesis"

Lin Fritschi
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My Curtin work days are Mondays, Tuesdays and Wednesdays.

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CRICOS Provider Code 00301J

From: Ben Mullins <B.Mullins@curtin.edu.au>
Sent: Friday, 28 October 2022 6:39 AM
To: Lowry, David (RTIO) <David.Lowry@riotinto.com>; Ben Mullins <B.Mullins@curtin.edu.au>
Subject: [External] RE: Permission to include co-authored papers in PhD thesis

Hi Dave,
Yes of course I give you permission.
Ben.

Ben Mullins
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From: Bec O'Leary <bec.oleary@curtin.edu.au>
Sent: Thursday, 20 October 2022 11:58 AM
To: Lowry, David (RTIO) <David.Lowry@riotinto.com>
Subject: [External] Re: Permission to include co-authored papers in PhD thesis

Hi Dave
I give you permission to include the papers that I have co-authored in your PhD thesis.

Dr Rebecca O'Leary
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Appendix C: Copyright information for published articles

Copyright information: Occupational noise exposure of utility workers using task based and full shift measurement comparisons (Chapter 4)

Occupational noise exposure of utility workers using task based and full shift measurement comparisons - ScienceDirect

Copyright information: Use of expert elicitation in the field of occupational hygiene: comparison of expert and observed data distributions (Chapter 5)

Use of expert elicitation in the field of occupational hygiene: Comparison of expert and observed data distributions | PLOS ONE

Appendix D: Questionnaire, participant information and consent form for survey of occupational hygienists (Chapter 3)

Curtin University

PARTICIPANT INFORMATION

Research project: Occupational hygiene decision-making: practice variation and experience, training, and education determinants
(HREC approval number: HRE2021-0156)

What is the research project about?

The concepts of professional judgement and decision-making underpins the way in which an occupational hygienist assesses an exposure problem. Despite the importance placed on professional judgement in the discipline, a method of assessment to characterise the determinants of decision-making in the domain of occupational hygiene has not been available. This pilot project is aimed at identifying the key decision-making determinants employed by occupational hygienists and is focused on 'practice variation' amongst hygienists and assessing the degree to which experience, training and education have on exposure assessment.

Who is doing the Research?

The project is being conducted by David Lowry (MAIOH, COH) under the academic supervision of Professor Lin Fritschi and Associate Professor Ben Mullins. The results of this research project will be used to obtain a Doctor of Philosophy at Curtin University and is funded by the University. There will be no costs to you, and you will not be paid for participating in this project.

Why am I being asked to take part and what will I have to do?

You have been asked to take part in this research because you are a member of the Australian Institute of Occupational Hygienists (AIOH) which is the target population for this study. Your participation will involve the completion of an online survey consisting of 31 questions which is anticipated to take 15 - 20 minutes to complete. The survey will be delivered by the online survey platform, Qualtrics. The questions focus on professional judgement and decision-making with respect to exposure assessment. The information collected will be de-identified prior to analysis.

Are there any benefits to being in the research project?

In addition to the opportunity to take part in a research study, the project will provide you with an opportunity to describe your experience with respect to your own application of professional judgement in the course of your career as an occupational hygiene professional. The outcomes of the project may help guide future efforts in training, education, and awareness for practising occupational hygienists.

Are there any risks, side-effects, discomforts, or inconveniences from being in the research project?

There are no foreseeable risks from this research project. Apart from giving up your time, we do not expect that there will be any risks or inconveniences associated with taking part in this study.

Who will have access to my information?

As an incentive to participate, we will be holding a prize draw for 4 participants to be selected at random to receive a gift voucher. We will ask for your name and email address when we collect the data, to allow us to contact you if you are the winner of our prize draw, and also to write to you and provide you with a copy of the results of the research you have participated in. There will also be an option to complete the survey without providing your contact details. After the prize draw, we will remove all identifying information from the data. That means the data we analyse and the data we store will be non-identifiable, and we will have no way to identify your information. Electronic data will be password-protected. The information we collect in this study will be kept under secure conditions at Curtin University for 7 years after the research is published. The results of this research may be presented at conferences or published in professional journals. You will not be identified in any results that are published or presented.

Will you tell me the results of the research?

We will write to you at the end of the research and let you know the results of the research. Results will not be individual but based on all the information we collect and review as part of the research.

Do I have to take part in the research project?

Taking part in a research project is voluntary. If you decide to take part and then change your mind, that is okay, you can withdraw from the project.

What happens next and who can I contact about the research?

If you decide to take part in this research, we will ask you to provide consent. By providing consent it is telling us that you understand what you have read in this document and are happy to take part. Please take your time and ask any questions you have before you decide to participate. At the start of the survey there is a checkbox to indicate that you have understood the information provided in this document. If you have any questions regarding the study, please contact David Lowry on david.lowry1@postgrad.curtin.edu.au

Curtin University Human Research Ethics Committee (HREC) has approved this study (Approval number: HRE2021-0156). Should you wish to discuss the study with someone not directly involved, in particular, any matters concerning the conduct of the study or your rights as a participant, or you wish to make a confidential complaint, you may contact the Ethics Officer on (08) 9266 9223 or the Manager, Research Integrity on (08) 9266 7093 or email hrec@curtin.edu.au

Participant consent:

☐ I have received information regarding this research and had an opportunity to ask questions. I believe I understand the purpose, extent and possible risks of my involvement in this project and I voluntarily consent to take part.

Overarching theme: Occupational hygiene decision making: experience, training and education determinants

Key question: What are the key decision-making determinants employed by occupational hygienists?

Sub-questions:

1. What is the practice variation between hygienists? (i.e. what process is followed, what do hygienists 'look out' for)
2. Does this change based on agent being assessed?
3. Does perception of risk = potential of risk?
4. What bearing does experience, training and education have on exposure assessment?

Definitions:

Professional judgement: *the application of knowledge and experience in defining objectives, solving problems, establishing guidelines, reviewing the work of others, interpreting results and providing and assessing advice or recommendations and other matters which have an element of latitude or decision-making*

Exposure assessment: *the process of characterising, estimating and measuring the magnitude, frequency, and duration of contact with an agent as well as the number and characteristics of the population exposed*

Exposure modelling: *incorporating human activity patterns to determine contact with environmental toxicants in a defined framework*

Decision statistic: *a value or parameter by which an exposure data is assessed against to determine risk acceptability. For example, estimated arithmetic mean, one-side upper and lower confidence limits of the arithmetic mean, 95th percentile, upper tolerance limit*

Heuristic: *a simple, efficient rule used to arrive at a decision, make a judgment or solve a problem, typically when faced with a complex problem or incomplete information. Three primary heuristics –*

1. *Anchoring and adjustment – starting from a readily available number—the "anchor"—and shifting either up or down to reach an answer that seems plausible*
2. *Availability – how likely or how frequent an event is based on its availability*
3. *Representativeness - the use of a category to arrive at a decision*

Experience and work history

The concepts of professional judgement and decision-making underpins the way in which an occupational hygienist assesses an exposure problem. This pilot project is aimed at identifying the key decision-making determinants employed by occupational hygienists, and is focused on 'practice variation' amongst hygienists and assessing the degree to which experience, training and education have on exposure assessment. The project is being conducted by David Lowry (MAIOH, COH) under the academic supervision of Professor Lin Fritschi and Associate Professor Ben Mullins through Curtin University in Western Australia.

Your participation will involve the completion of an online survey consisting of 33 questions which is anticipated to take 15 minutes to complete. The questions focus on professional judgement and decision-making and your involvement will provide you with an opportunity to describe your experience with respect to your own experience in the course of your career as an occupational hygiene professional. There are no foreseeable risks from this research project. Apart from giving up your time, we do not expect that there will be any risks or inconveniences associated with taking part in this study. The outcomes of the project may help guide future efforts in training, education and awareness for practising occupational hygienists.

As an incentive to participate, we will be holding a prize draw for 4 participants to be selected at random to receive a gift voucher. We will ask for your name and email address at the beginning of the survey to allow us to contact you if you are the winner of our prize draw, and also to write to you and provide you with a copy of the results of the research you have participated in.

For further information on the research, or if you have any questions in relation to this study, please contact David Lowry on david.lowry1@postgrad.curtin.edu.au

I have received information regarding this research and had an opportunity to ask questions. I believe I understand the purpose, extent and possible risks of my involvement in this project and I voluntarily consent to take part.

- ◯ Yes
- ◯ No

Thank you for taking the time to participate in this survey. The survey consists of 33 questions and will take approximately 15 minutes to complete.

Please select whether you agree to provide your name and email address if you would like the opportunity to be selected for one of 4 gift vouchers and would also like to recieve a copy of the research results once complete.

- ◯ Prefer not to provide my contact details
- ◯ Happy to provide my contact details (please provide name and email below):

In which country do you live?

How would you best describe your current job role?

- ◯ Occupational Hygienist
- ◯ Health, Safety & Environment Professional
- ◯ Consultant
- ◯ Other (please provide below)

How long have you practiced as an occupational hygienist, or have had occupational hygiene accountability in your role?

- ◯ <5 years
- ◯ 5 – 10 years
- ◯ 10 – 20 years
- ◯ >20 years

What is your age bracket?

- ◯ 20 – 30 years
- ◯ 30 – 40 years

- 40 – 50 years
- > 50 years
- Prefer not to say

Which sector are you employed by?

- Private Industry
- Government
- Consultancy
- Academia
- Other (please list)

Which industry are you employed by?

- Mining
- Oil and Gas
- Agriculture
- Manufacturing
- Construction
- Chemical
- Other (please list)

Do you have a specific area of practice / expertise? (i.e. generalist, noise, ventilation etc.). Please list:

Are you a certified hygienist under an International Occupational Hygiene Association (IOHA) association scheme?

- Yes
- No

Have you ever given a conference presentation?

- Yes
- No

Have you ever published a paper in a peer reviewed journal?

- Yes
- No

raining and education

What is your highest level of tertiary degree?

- Bachelors degree
- Masters degree
- Doctor of Philosophy
- Other (please list)

What was the focus of your tertiary degree(s). Please list:

Other than in your formal tertiary studies, have you undertaken any training in risk communication?

◯ Yes

◯ No

Other than in your formal tertiary studies, have you undertaken any training in how to model data, or interpret complex data?

◯ Yes

◯ No

Have you ever received technical mentoring, either formal or informal, in how to model data, or interpret complex data?

◯ Yes

◯ No

ʔrofessional judgement and decision making

For this section of the survey, some definitions used are provided below to help guide your responses.

Professional judgement: the application of knowledge and experience in defining objectives, solving problems, establishing guidelines, reviewing the work of others, interpreting results and providing and assessing advice or recommendations which have an element of decision-making

Exposure assessment: the process of characterising, estimating and measuring the magnitude, frequency, and duration of contact with an agent as well as the number and characteristics of the population exposed

Decision statistic: a value or parameter by which exposure data is assessed against to determine risk acceptability. For example, estimated arithmetic mean, one-side upper and lower confidence limits of the arithmetic mean, 95th percentile, upper tolerance limit

'Rule of thumb' definitions:

1. Anchoring and adjustment: can occur when we begin from a readily available number - the 'anchor' - and we shift either up or down to reach an answer that seems plausible
2. Availability: can occur when we make a judgement about a situation on the basis of the examples of similar situations that come to mind, allowing us to extrapolate to the situation in which we find ourselves
3. Representativeness: can occur when we evaluate the probability of an event based on its similarity to another event. In general, we tend to overestimate the likelihood of an event occurring based on its perceived similarity with another event

What percent of time in your current role do you use professional judgment to assess exposure risk?

◯ <25%

◯ 25 – 50%

◯ 50 - 75%

◯ >75%

What percent of time in your current role is focused on exposure assessment?

◯ <25%

◯ 25 – 50%

◯ 50 - 75%

◯ >75%

How experienced are you in dealing with 'high stakes' risk communication (i.e. expert witness testimony, community outrage, adverse media attention, industrial relations issues)?

◯ Very experienced

◯ Somewhat experienced

◯ Never undertaken

What goal/s are you looking to achieve when you complete an exposure assessment? Please list:

Below is an outline of one process that can be used to ascertain an exposure profile. Reflecting on your own approach, to what extent do you agree with the below process?

1. *Identify the Similar Exposure Group (SEG) to profile*
2. *Randomly select workers and exposureperiods within the selected SEG*
3. *Collect samples of the randomly selectedworkers at randomly selected time periods*
4. *Calculate the descriptive statistics for the data set*
5. *Determine if the data fits a lognormal and/or normaldistribution*
6. *Make a decision on the acceptability of the exposureprofile*
7. *Refine the SEG, if necessary*
8. *Advise on control based on exposure profile acceptability*

- Strongly agree
- Somewhat agree
- Disagree

For the previous question, if you answered 'somewhat agree' or 'disagree' how would you amend the exposure assessment process? Please list:

Generally speaking, how would you describe your approach to occupational hygiene decision-making?

- Intuitive and subconscious
- Analytical and conscious

Do you alter your exposure assessment approach depending on the agent of interest?

- Yes
- No

Do you alter your exposure assessment approach depending on the size of the organisation you are working within? (i.e. different approach taken for small and medium enterprises, as opposed to a large company)

- Yes
- No

Do you consider any ethical implications that may be invovled when conducting an exposure assessment?

- Definitely yes
- Probably yes
- Might or might not
- Probably not
- Definitely not

What tools do you commonly use when completing an exposure assessment? Please list:

When assessing measured data, what decision statistic(s) do you use to assess acceptability of exposure? Please list:

In the absence of quantitative (measured) data, how comfortable are you in making an exposure judgement?

- Extremely comfortable
-

Somewhat comfortable

- ◯ Neither comfortable nor uncomfortable
- ◯ Somewhat uncomfortable
- ◯ Extremely uncomfortable

In the absence of quantitative (measured) data, what other sources of information do you rely upon to make an exposure judgement? Please list:

How comfortable are you in communicating an exposure risk to a worker or client in the absence of quantitative (measured) data?

- ◯ Extremely comfortable
- ◯ Somewhat comfortable
- ◯ Neither comfortable nor uncomfortable
- ◯ Somewhat uncomfortable
- ◯ Extremely uncomfortable

Decision-making when uncertainty exists can often be aided by the use of a 'rule of thumb' to arrive at an exposure determination. To what extent do you believe you have used such a technique?

- ◯ Used regularly
- ◯ Used occasionally
- ◯ Never used

For the previous question, if you answered 'used regularly' or 'used occasionally', which rule do you recall utilising most often? (Please refer to applicable definitions)

- ◯ Anchoring and adjustment
- ◯ Availability
- ◯ Representativeness

What resources do you use to complement your professional judgment?

- ◯ Peer reviewed journals
- ◯ Technical papers
- ◯ Government websites
- ◯ Professional networks
- ◯ Other (please list)

Appendix E: AIOH 2022 Conference proceedings excerpt – Chapter 3

DOES PRACTICE VARIATION IN EXPOSURE ASSESSMENT EXIST AMONGST OCCUPATIONAL HYGIENISTS?

David Lowry and Lin Fritschi

Abstract

Objectives: Occupational hygienists regularly make decisions relating to worker exposure based on professional judgement, usually in the absence of quantitative data and in the presence of high uncertainty. These factors have the potential to lead to practice variation in the form of deviation from established guidelines or protocols. In this paper, we describe practice variation amongst a group of occupational hygienists to ascertain similarities and differences in approach to exposure assessment.

1. Methods

A link to a survey was sent to members of three accreditation bodies – Australian Institute of Occupational Hygienists (AIOH), British Occupational Hygiene Society (BOHS), American Industrial Hygiene Association (AIHA) – inviting occupational hygienists to complete an online questionnaire. This questionnaire included questions relating to exposure assessment, professional judgement, decision-making and use of statistics, in addition to demographic characteristics such as experience, training and education.

2. Results

A total of 140 occupational hygienists completed the questionnaire. Evidence of practice variation was found across the areas of decision-making, agent of interest, size of organisation being assessed, ethical implications, and agreement with a standardised exposure assessment protocol. The issues of randomised sampling, hazard identification, task-based exposure monitoring, and organisational size and funding were identified as areas of focus for the respondents.

3. Conclusions

These findings suggest that further assessment of the extent to which variation exists is needed. Further efforts should assess occupational hygienist's decision-making processes and attitudes when deviating from established guidelines or protocols, as well as development of methods and frameworks to determine when variation is unwarranted and change is justified.

Presenter Bio – David Lowry

David Lowry is a passionate Certified Occupational Hygienist (COH) and full member of the Australian Institute of Occupational Hygienists (AIOH) with 15 years' experience in managing complex health risk across a range of industries. Beginning his career as an environmental scientist, David focused on water and wetlands management, before pivoting to focus on the management of human health risk. David worked in consultancy and for other mining operators before eventually joining Rio Tinto in 2012. During his time with Rio Tinto, David has worked across both mining operations and supply chain, and currently holds the role of Principal Occupational Hygienist supporting all Western Australian assets. David has advised operational leaders across Rio Tinto's range of commodities including aluminium refining and smelting; iron ore, bauxite, salt, copper and diamond mining; and titanium dioxide and mineral sands processing within Australia (Western Australia, Queensland, Northern Territory, Tasmania), South Africa (Richards Bay), and Canada (various operations in Quebec). David holds BSc degrees in Biological Science and Occupational Therapy and is currently undertaking a PhD focusing on professional judgement and decision making in the field of occupational hygiene. David has presented original research at several scientific conferences and holds an adjunct appointment as Senior Lecturer at Edith Cowan University's School of Medical and Health Sciences in Western Australia. In his spare time, David enjoys surfing, running, playing guitar and spending quality time with his wife and two young children.

Appendix F: Published paper 1 (Chapter 4)

Heliyon 8 (2022) e09747

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Occupational noise exposure of utility workers using task based and full shift measurement comparisons

David Michael Lowry *, Lin Fritschi, Benjamin J. Mullins

School of Population Health, Curtin University, Perth, WA, Australia

ARTICLE INFO

Keywords:
Occupational hygiene
Exposure
Noise
Dosimetry

ABSTRACT

Introduction: The main purpose of this study was to determine if a combination of area noise measurements and task activity diaries give a reasonable estimate of full-shift dosimeter measurements in a cohort of utility workers. Few studies have been conducted to evaluate the efficacy of using task-based noise exposures to estimate full shift time weighted average (TWA) noise exposures.

Methods: Estimates of full shift time TWA noise exposures for a group of utility workers (n = 224) were calculated using dosimeter measurements. Area noise measurements using a sound level meter were used to recreate the TWA for each personal dosimetry sample based on detail provided in the task activity diary for each sample. Full shift TWA noise exposures were compared to corresponding area noise measurements using simple linear regression analysis.

Results: Associations between full shift TWA measurements and task-based area measurements were closely associated, with R^2 values above 0.85 for all job roles.

Discussion: Task-based noise exposure analysis has the potential to be widely used in the utilities industry. While full-shift monitoring to determine TWA exposures is useful, the changing work environment, variability in tasks and equipment, and varying workday hours, limit the ability of the 8-hr TWA to accurately characterise the exposures and associated health risks for utility workers.

1. Introduction

Exposure to noise constitutes a significant health risk in the occupational environment. There is sufficient scientific evidence indicating that excessive and prolonged noise exposure can induce hearing impairment, hypertension and ischemic heart disease, sleep disturbance and general annoyance [1]. A number of studies have also suggested a positive relationship between excessive noise exposure and susceptibility to occupational injuries [2] as well as increased risk of further hearing deterioration [3]. In addition, whilst noise is considered a physical factor for damage to the cochlea, combined exposure to noise and certain chemical substances – collectively referred to as ototoxins - can impair the cochlea, the vestibulo-cochlear apparatus, the eighth cranial nerve or the central nervous system [4]. Excessive noise exposure in high temperatures may also present a high risk for noise induced hearing loss (NIHL) [5].

Methods for assessing occupational noise exposure have largely focussed on full-shift TWA sampling conducted on workers, however task-based methods have an advantage over full-shift methods in that they provide a more direct understanding of the primary sources of high noise exposure [6]. This has a benefit not only in targeting effective noise control interventions in the workplace, but also in estimating exposure levels for a range of task combinations. Task-based measurements can also allow for the characterisation of full-shift exposure whilst also permitting assessment of short-term hazards which might not be identified through a standard full-shift exposure sampling protocol [7]. Taking measurements at the task level has been shown to be a useful method for determining hazardous exposures in complex dynamic environments [8]. Furthermore, epidemiologic studies benefit from task-based exposure assessments because they support the validity of cumulative exposure histories by limiting misclassifications which can occur when reconstructing past exposures through employment records or work histories [9].

Characterisation of noise exposure for workers who undertake tasks in varied occupational settings and conditions is especially challenging, given the changing work environment in which these professions operate. Therefore, a realistic measure of noise dose utilising full-shift measurements alone would not be expected to be representative of true

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https://doi.org/10.1016/j.heliyon.2022.e09747
Received 4 April 2022; Received in revised form 19 May 2022; Accepted 15 June 2022

exposure experienced over a typical shift. In addition, full-shift TWA measurements do not provide information that can be used to identify the source of intense noise exposures experienced. Therefore, determination of noise exposures at the task level for utility workers may be more useful, particularly when developing effective engineering controls to reduce exposure and prevent NIHL. One such group are utility workers, whose highly variable tasks and working conditions present a range of potential occupational noise exposures. Utility workers perform a wide variety of semi-skilled and skilled maintenance duties in the installation, construction, repair, and general maintenance of electrical, water, communications, and power generation assets. Workers who fall into this group are typically trade-qualified and occupy five distinct job roles – electrician, plumber, communication technician, fuel delivery driver and power station operator. In Australia, approximately 144,200 persons were employed in the utilities industry in 2020 [10].

Task based exposure assessment strategies have previously been employed for workplace chemical exposures [7, 8, 11, 12] and occupational noise [13, 14, 15, 16, 17]. However, only three peer-reviewed studies could be found directly comparing full shift and task-based estimates of exposure to noise (summarised in Table 1). These studies demonstrate that the accuracy of the exposure assessments depend on how well tasks are defined and the ability of statistical models to account for variability in noise exposures. As an example, clearly defining beginning and ending times for each task increases the agreement between estimated and measured daily noise exposures. The studies also indicate there is generally agreement between time-at-task information collected from direct observation and worker self-reports [18, 19, 20] Overall, the studies found moderate to good agreement between measured and task-based estimated daily noise exposures.

The main purpose of this study is to determine if a combination of area noise measurements and task activity diaries give a reasonable estimate of full-shift dosimeter measurement in a cohort of utility workers.

2. Methods

2.1. Personal noise dosimetry

Personal sampling data were collected with the assistance of personnel from a registered utility responsible for providing the critical services of electrical generation and distribution, water and wastewater, hydrocarbons, and communications to a number of mining operations and five townships located in the Pilbara region in North-Western Australia. The inclusion criteria for this study were personnel employed by the utility in the job categories of electrician, plumber, communications technician, and power station operator. A stratified sampling method was employed and the number of employees to sample was calculated as outlined in Table A-2 of the NIOSH publication *Occupational exposure sampling strategy manual* [22]. Personal noise samples were collected and analysed as per *AS/NZS 1269-2005 Occupational Noise Management – Part 1* [23]. Workers were selected randomly whenever possible using a random number table.

Equipment used to conduct noise sampling consisted of personal noise dosimeters (type 4448, Brüel and Kjær, Nærum, Denmark) calibrated pre and post sampling with a sound calibrator (type 4231, Brüel and Kjær, Nærum, Denmark). No significant shift in calibration was detected for any individual measurement. The dosimeters measured sound pressure levels in decibels (dB) using an 'A' frequency weighting, and the measuring range was 50–140 dB (L_{Aeq}) using no additional threshold level and a 3-dB exchange rate. The dosimeters logged noise data each minute and $L_{Aeq,T}$ for the total duration of the measurement period was stored. Sampling times were representative of working periods of individuals monitored, which were at least eight hours of a twelve-hour shift. A total of 224 dosimeter measurements were captured.

Participants were instructed to keep track of their activities during the day and to fill out a logbook on their time spent at different tasks during the measurement period. In addition, participants were asked to state their use of hearing protection devices.

Table 1. Summary of peer reviewed studies comparing full shift and task-based estimates of exposure to noise.

Study aim	Methods and results	Key findings
To evaluate the agreement between task-based estimated and full-shift noise exposures [6].	Task-based noise exposures from 189 subjects on 502 work shifts were used in six linear regression models to obtain estimates of full-shift noise exposures. These models varied in complexity, from estimates using task-based noise exposures alone to estimates using task-based noise exposures grouped by equipment, work location and trade. Agreement between task-based estimates and measured full-shift noise exposures ranged from an $R^2 = 0.11$ to an $R^2 = 0.90$.	The study found that the R^2 increases when the specificity of the task definitions increases. This study also found that task-based estimates of full-shift exposure include a high degree of error when the task-based noise exposures are highly variable.
To validate the accuracy of construction worker recall of task and environment based information; and to evaluate the effect of task recall on estimates of noise exposure [18, 19, 20].	A cohort of construction workers (n = 25) had noise exposures measured by dosimeters, and time-at-task information recorded on activity cards or questionnaires. Simple linear regression was used to determine the agreement between the task-based estimated and dosimetry measured daily noise exposures. The relationship between dosimeter measured daily noise exposures and task based estimated daily noise exposures calculated from activity cards and questionnaires had an $R^2 = 0.62$, and $R^2 = 0.59$ respectively.	Six months after tasks were performed, construction workers were able to accurately recall the percentage time they spent at various tasks. Estimates of noise exposure based on long term recall (questionnaire) were no different from estimates derived from daily activity cards and were strongly correlated with dosimetry measurements, overestimating the level on average by 2.0 dB(A).
To compare estimated and measured daily noise exposures [21].	Eight estimates of daily noise exposures were calculated for each dosimeter measured daily noise exposure (n = 189). Estimates were calculated using time-at task data collected by direct observation, worker diary, and supervisor summary. Estimated daily noise exposures were calculated using either the arithmetic or geometric mean task-based noise exposures. Agreements between estimated daily noise exposure and measured daily noise exposures ranged from 0.70 – 0.77 for direct observation, 0.63–0.71 for worker reports, and 0.49–0.62 for supervisor assessments.	The study found that a high degree of agreement can be achieved between task-based and dosimetry-based estimates of full-shift exposures. The task-based approach that uses worker reports combined with task AM or GM levels yielded similar results to the more time-intensive direct observation method to estimate full-shift exposures.

2.2. Calculation of personal noise dosimetry measurements

For the different job categories the mean $L_{Aeq,T}$ measured with dosimeters was calculated. Using the equation $E_1 = (10^{(LAeq/10)}) * T$ with L_{Aeq} being the equivalent noise level measured by the dosimeter and T the duration of the dosimeter measurement, an exposure value (E_1) for each dosimeter measurement was calculated. For each job category, the mean $L_{Aeq,T}$ measured by the dosimeters was calculated using the equation $L_{Aeq,12h} = 10 * \log((E_1 + E_2 + \ldots)/12h)$, where 12h was replaced with the sum of the durations of the dosimeter measurements in hours. 224 complete and independent full-shift personal measurements were made for the analysis.

2.3. Area noise measurements

Area noise measurements were made based on the task details outlined in each corresponding full-shift personal sample to replicate full-shift exposure. Area measurements of noise levels were conducted in accordance with *AS/NZS 1269-2005* [23] using a sound level meter (hand-held analyser type 2250, Brüel and Kjær, Nærum, Denmark). A similar method of sample collection is detailed in ISO 9612 wherein the sound level meter microphone is positioned at the location of the worker's head during normal performance of a job or task [24].

In each measurement position, 45-second measurements were completed, and A-weighted equivalent noise levels ($L_{Aeq,45s}$) were recorded. The area measurements were limited to locations where the utility personnel are likely to spend time during the course of planned or unscheduled maintenance work, based on the observations made within the corresponding full-shift measurement task activity logbook. A member of the work group was present at each location to demonstrate typical distances from noise sources. With the worker in position, the sound level meter microphone was located approximately 0.1 m horizontally from the entrance of the external canal of the ear receiving the noise level. The measurement duration of an individual source was sufficiently long for the noise exposure level to be representative of the activities being performed by the worker as required to obtain an L_{eq} reading which had stabilised within ±0.5 dB.

2.4. Calculation of area noise measurements

Mean, median and percentiles of noise levels were calculated for each measurement location. The quantity used for averaging the results was calculated from the measured $L_{Aeq,45s}$ by,

$$\frac{p2}{p02} = \left(\frac{LAeq,45s}{10}\right) \tag{1}$$

where p is the sound pressure that corresponds to $L_{Aeq,45s}$ and p_0 is a reference value set at 20 μPa. The corresponding mean sound pressure level was calculated as,

$$\overline{LAeq,45s} = 10 \ \log \left(\frac{p}{p0}\right)^2 \tag{2}$$

The task based estimated $L_{Aeq,12h}$ was calculated based on mean noise levels during typical working conditions. For each measurement location, an exposure value (E_1) was calculated as,

$$E_1 = (10^{(LAeq/10)}) * T \tag{3}$$

where L_{Aeq} is the mean noise level at the location, and T is the mean hours spent at that location during a 12 h shift for each job category. The exchange rate used in the equation is 3 dB. $L_{Aeq,12h}$ for each job category was then calculated as,

$$L_{Aeq,12h} = 10 * \log((E_1 + E_2 + \ldots)/12h) \tag{4}$$

The fit to the data uses the following equation and is calculated as,

$$dB(A)_D = M * dB(A)_T + C \tag{5}$$

Where M is the slope of the line and C is the intercept. T is the mean hours spent at the task location.

2.5. Comparison of full-shift dosimeter measurements and area measurements

Each full-shift measurement was broken down to the task level through the review of its corresponding task activity diary. Tasks were assessed in the field using a sound level meter to recreate the exposure measured in the full-shift sample. This exercise was repeated for all personal measurements across all five job roles. An example is shown in Table 2.

2.6. Statistical analysis

All calculations and descriptive statistics were completed using IHSTAT (https://www.aiha.org/public-resources/consumer-resources/apps-and-tools-resource-center) an exposure statistics application developed by the American Industrial Hygiene Association (AIHA). IHSTAT is an Excel application capable of calculating exposure statistics with the use of lognormal (or normal) parametric statistics. Simple linear regression analysis was conducted using Stata version 15 (StataCorp LP) to compare full-shift and task-based methods of exposure assessment.

Table 2. Evaluation of normalised daily noise exposure using forty five second long average noise levels $L_{Aeq,T}$ by observed task activity (Electrician job role example).

Sample 005 – Activity: Asset Inspection and Equipment Repair

Task	*Measured Noise Level L Aeq,Ti*	*Duration of Exposure Ti*	*Pascal Squared*	*Partial Noise Exposure E A,Ti*	*Total Daily Noise Exposure E A,T*	*Normalised Noise Exposure Level L Aeq,8h*
	dB(A)	*Hours*	*Pa 2*	*Pa 2h*	*Pa 2 h*	*dB(A)*
TP1 inspection - near louvers	88.50	0.15	0.283	0.042		
TP2 inspection - near louvers	90.90	0.15	0.492	0.074		
TP3 inspection - near louvers	91.70	0.15	0.592	0.089		
In between louvers	83.20	0.10	0.084	0.008		
Yale Vendor Forklift with beeper	92.90	0.15	0.780	0.117		
Pedestal Grinder	91.90	0.15	0.620	0.093		
Sander	85.20	0.15	0.132	0.020		
16oz shot peen hammer	112.10	0.05	64.872	3.244		
Breaks and other Activities	65.00	11.45	0.001	0.014		
					3.701	91

Table 3. Descriptive statistics from personal noise dosimetry results.

Job Role	Number of samples taken (n)	Geometric Standard Deviation (GSD)	Mean		Maximum		Minimum	
			% dose	dB(A)	% dose	dB(A)	% dose	dB(A)
Fuel Delivery Driver	39	3.279	60.723	82.84	444.3	91.46	3	69.82
Communications Technician	35	3.863	12.03	75.83	55.5	82.45	0.3	59.84
Electrician	50	3.331	41.18	81.16	243.7	88.86	1.8	67.60
Plumber	50	3.128	41.42	81.19	267.3	89.26	0.4	61.10
Power Station Operator	50	3.535	26.43	79.24	150	86.75	0.2	58.10

3. Results

The mean dB(A) from the full-shift TWA measurements was below the occupational exposure limit (OEL) for all job roles (Table 3). However, the maximum level was above the OEL for all job roles except the communications technician.

The simple linear regression analysis indicated excellent agreement between the task-based and full-shift measurements (Figures 1, 2, 3, 4, and 5) with R^2 values above 0.85 for all job roles. For all job roles, the simple linear regression analysis calculated a coefficient of determination of 0.91 for the agreement of full-shift and task-based measurements showing a good fit for the model against the data (Figure 6). The fit to the data is of the form $dB(A)_D = M * dB(A)_T + C$. A summary of fits and R^2 values is given in Table 4.

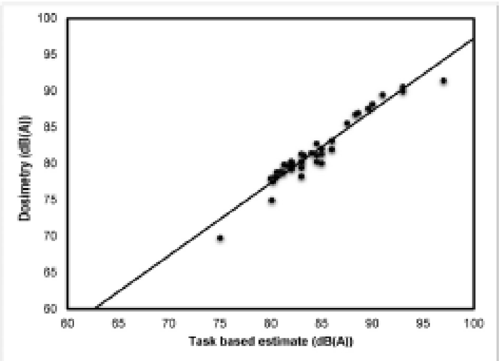

Figure 1. Comparisons of full-shift noise dosimetry with task-based estimates using area measurements for job role Fuel Delivery Driver.

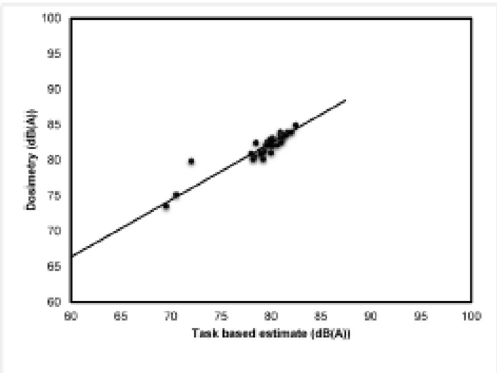

Figure 2. Comparisons of full-shift noise dosimetry with task-based estimates using area measurements for job role Communications Technician.

4. Discussion

The current study aimed to investigate exposure to occupational noise as experienced by utility workers using a combination of area noise measurements and task activity diaries to reasonably estimate full-shift dosimeter measurements. The results of this study indicate that task-based estimates of noise exposure can be useful in forecasting full-shift noise exposure, when calculated using specific tasks undertaken by job role. The coefficients of determination for all five job roles indicated agreement between full-shift dosimeter measurements and estimates made using area measurements. Considering the variability in the tasks described in the task activity diaries, the task-based estimates are likely to fall within the expected range, providing a good estimate for daily noise exposures.

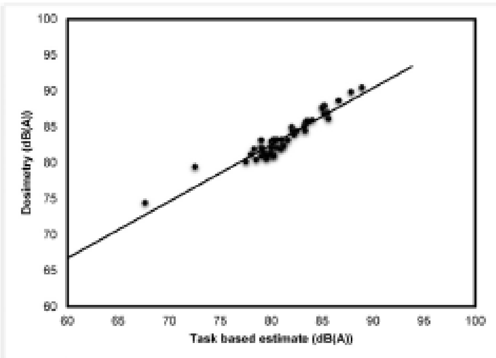

Figure 3. Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for job role Electrician.

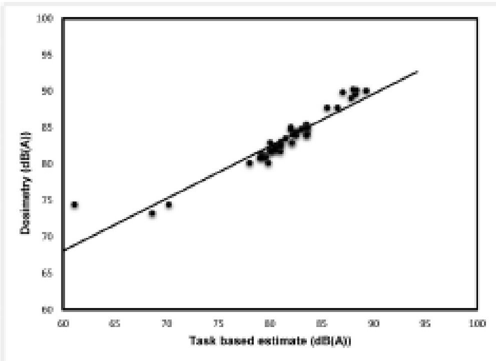

Figure 4. Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for job role Plumber.

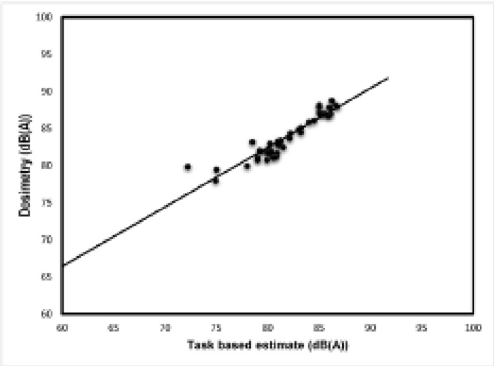

Figure 5. Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for job role Power Station Operator.

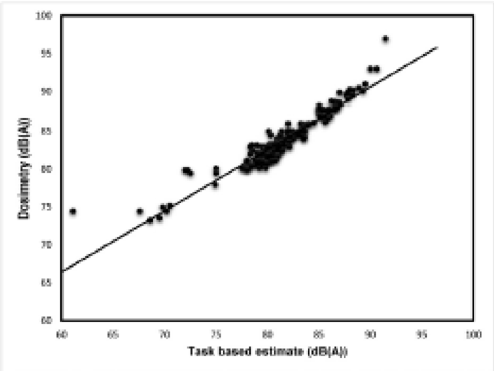

Figure 6. Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for all job roles.

Table 4. Summary of simple linear regression fits and R^2 values by job role.

Job Role Dataset	M	C	R^2
Fuel Delivery Driver	0.996	2.334	0.932
Communications Technician	0.803	18.184	0.935
Electrician	0.788	19.466	0.888
Plumber	0.719	24.884	0.885
Power Station Operator	0.800	18.416	0.936
Combined Dataset	0.806	18.049	0.911

The three studies in the literature comparing full shift and task-based estimates of exposure to noise [6, 18, 21] highlighted that clearly defining beginning and ending times for each task increases the agreement between estimated and measured daily noise exposures, and there is generally agreement between time-at-task information collected from direct observation and worker self-reports. In general, these studies found moderate to good agreement between measured and task-based estimated daily noise exposures. In estimating task-based exposure to noise, the definition of *task* is paramount. A task can be described as an overall activity, whereby a set of sub-tasks may be present, or can be described at the sub-task level in first instance. For the purpose of accuracy, the more specific the description of the task to be measured, the better the precision in assessing the task, and hence the more credible the output data of the task-based measurement taken [6].

The current study demonstrates that, provided a task is defined accurately with the assistance of the operator completing the task, then assessment of these tasks can also be accurate enough to accommodate variability between tasks in a dynamic environment. A worker's input into tasks completed on a day that they were sampled is crucial to understanding the key elements of the worker's shift that may have contributed to exposure values measured. This information is known to be unreliable when collected retrospectively [13], therefore the task activity diaries within this study were completed with each worker directly after their shift to increase task recall accuracy. This appears to be a key point of difference in the agreement between area and personal measurements within the context of this study (ranging 0.885–0.936), compared to other studies [6, 12, 13].

From a practical standpoint, the good correlation demonstrates that the calculation given ($dB(A)_D = M * dB(A)_T + C$) provides an equivalency factor between dosimetry and area measurements for noise. The fitted equations, given the strong agreement between individual job roles and to the whole dataset, suggest that this calculation may work for all occupations and provide a standard agreement between the two methodologies dependent on equipment utilised. The implication for the occupational hygienist is that, providing task characterisation is accurate, TWA exposures have the potential to be accurately characterised utilising a static sampling method, meaning statistically valid representation across multiple members of a work group over a fixed period may not be necessary to estimate noise exposure.

5. Conclusion

This work builds upon similar research conducted by Seixas et. al [6] and Virji et al [21] wherein the agreement between task-based estimated and full-shift noise exposures and comparisons between estimated and measured daily noise exposures were assessed respectively. Both studies found that agreement can be observed between task-based and full-shift estimates, however this is largely contingent on factors such as specificity of task definition and worker reports [6, 21]. Building upon these determinants, the current study utilised worker input into tasks completed on the day that sampling was completed to increase task recall accuracy, and this appears to be a key factor in the agreement between area and personal measurements.

Task-based noise exposure analysis has the potential to be widely used in the utilities industry. While full-shift monitoring to determine TWA exposures is useful, the changing work environment, variability in tasks and equipment, and varying workday hours, limit the ability of the 8-hr TWA to accurately characterise the exposures and associated health risks for utility workers. For some utility providers, access to occupational hygiene services may be limited; meaning a complete noise survey conducted to determine personal exposures may not be viable. An alternative noise exposure analysis methodology, developed from a comprehensive task-based exposure database, is thus an attractive option for estimating the personal noise exposures of workers with irregular tasks, such as those in the utilities industry.

Declarations

Author contribution statement

David Michael Lowry: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Lin Fritschi and Benjamin J. Mullins: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

We would like to thank all the workers who participated in the sampling program.

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Appendix G: AIOH 2019 Conference proceedings excerpt – published paper 1 (Chapter 4)

Occupational noise exposure of utility workers using task based and full shift measurement comparisons

David Lowry (MAIOH, COH)

Background

- Exposure to noise constitutes a significant health risk in the occupational environment. There is sufficient scientific evidence indicating that excessive and prolonged noise exposure can induce hearing impairment, hypertension and ischemic heart disease, sleep disturbance and general annoyance (1)
- Methods for assessing occupational noise exposure have largely focussed on full-shift TWA sampling conducted on workers, however task-based methods have an advantage over full-shift methods in that they provide a more direct understanding of the primary sources of high noise exposure (2).
- Task-based measurements can also allow for the characterisation of full-shift exposure whilst also permitting assessment of short-term hazards which might not be identified through a standard full-shift exposure sampling protocol (3). Taking measurements at the task level has been shown to be a useful method for determining hazardous exposures in complex dynamic environments (4).
- The main purpose of this study is to determine if a combination of task based noise measurements and task activity diaries give a reasonable estimate of full-shift dosimeter measurement in a cohort of utility workers.

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Methods

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Sampling data were collected with the assistance of personnel from a registered utility responsible for providing the critical services of electrical generation and distribution, water and wastewater, hydrocarbons, and communications to a number of mining operations in North-Western Australia

Mean, median and percentiles of noise levels were calculated for each measurement location. The quantity used for averaging the results was calculated from the measured $L_{Aeq,45s}$ by,

$$\frac{p2}{p02} = \left(\frac{LAeq{,}45s}{10}\right) \qquad (1)$$

where p is the sound pressure that corresponds to $L_{Aeq,45s}$ and p_0 is a reference value set at 20 µPa. The corresponding mean sound pressure level was calculated as,

$$\overline{LAeq, 45s} = 10 \log \left(\frac{p}{p0}\right)^2 \qquad (2)$$

The task based estimated $L_{Aeq,12h}$ was calculated based on mean noise levels during typical working conditions. For each measurement location, an exposure value (E_1) was calculated as,

$$E_1 = \left(10^{(LAeq/10)}\right) * T \qquad (3)$$

Each full-shift measurement was broken down to the task level through the review of its corresponding task activity diary. A noise exposure calculation was conducted for each shift using the following steps:

1. Measurement of LAeqT for each task using sound level meter
2. Establish time spend completing each task (hours)
3. Calculate total LAeqT for whole shift (T hours)
4. Calculate A-weighted exposure EA,Ti for each task to give total EA,T and also highlight the main contributors to noise exposure
5. Calculate normalised total daily noise exposure LAeq8h
6. Add shift length adjustment (+1 dB given 12 hour shift pattern)

This exercise was repeated for all personal measurements across all five job roles

where L_{Aeq} is the mean noise level at the location, and T is the mean hours spent at that location during a 12 hour shift for each job category. The exchange rate used in the equation is 3 dB. $L_{Aeq,12h}$ for each job category was then calculated as,

$$L_{Aeq,12h} = 10 * \log((E_1 + E_2 + \ldots)/12h) \qquad (4)$$

The fit to the data uses the following equation and is calculated as,

$$dB(A)_D = M * dB(A)_T \qquad (5)$$

Results

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Table I. Descriptive statistics from personal noise dosimetry results

Job role	Number of samples (n)	Geometric standard deviation (GSD)	Minimum variance unbiased estimate (MVUE) (dB(A))
Fuel delivery driver	39	3.279	82.84
Communications technician	35	3.863	75.83
Electrician	50	3.331	81.16
Plumber	50	3.128	81.19
Power station operator	50	3.535	79.24

The Minimum Variance Unbiased Estimate (MVUE, dB(A)) from the full-shift TWA measurements was below the occupational exposure limit (OEL) for all job roles (Table I). However, the maximum level was above the OEL for all job roles except the communications technician

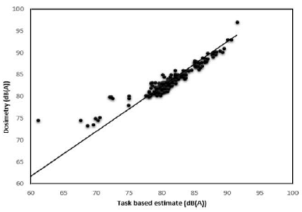

Figure 1. Simple linear regression model comparing full-shift noise dosimetry with task-based estimates using area measurements for all job roles

Table II. Summary of simple linear regression fits and R^2 values by job role

Job role dataset	M	R^2
Fuel delivery driver	0.968	0.932
Communications technician	1.034	0.858
Electrician	1.028	0.806
Plumber	1.025	0.725
Power station operator	1.026	0.861
Combined dataset	1.026	0.841

The simple linear regression analysis indicated good agreement between the task-based and full-shift measurements with R2 values above 0.72 for all job roles. For the combined dataset (all job roles), the simple linear regression analysis calculated a coefficient of determination of 0.84 for the agreement of full-shift and task-based measurements showing a good fit for the model against the data (Figure 1.). The fit to the data is of the form dB(A)D = M * dB(A)T. A summary of fits and R2 values is given in Table II.

Conclusions

- The results of this study indicate that task-based estimates of noise exposure can be useful in forecasting full-shift noise exposure, when calculated using specific tasks undertaken by job role
- The coefficients of determination for all five job roles indicated agreement between full-shift dosimeter measurements and estimates made using area measurements
- Taking into account the variability in the tasks described in the task activity diaries, the task-based estimates are likely to fall within the expected range, providing a good estimate for daily noise exposures
- The current study demonstrates that, provided a task is defined accurately with the assistance of the operator completing the task, then assessment of these tasks can also be accurate enough to accommodate variability between tasks in a dynamic environment
- The results indicate that this approach will produce a meaningful result for job roles with a relatively stable or predictable task load.

Appendix H: Published paper 2a (Chapter 5)

PLOS ONE

RESEARCH ARTICLE

Use of expert elicitation in the field of occupational hygiene: Comparison of expert and observed data distributions

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Citation: Lowry DM, Fritschi L, Mullins BJ, O'Leary RA (2022) Use of expert elicitation in the field of occupational hygiene: Comparison of expert and observed data distributions. PLoS ONE 17(6): e0269704. https://doi.org/10.1371/journal.pone.0269704

Editor: Aaron Specht, Harvard School of Public Health, UNITED STATES

Received: November 22, 2021

Accepted: May 25, 2022

Published: June 8, 2022

Data Availability Statement: All relevant data are within the manuscript and its Supporting Information files.

Funding: Funding provided by Rio Tinto. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

Abstract

The concept of professional judgement underpins the way in which an occupational hygienist assesses an exposure problem. Despite the importance placed on professional judgement in the discipline, a method of assessment to characterise accuracy has not been available. In this paper, we assess the professional judgement of four occupational hygienists ('experts') when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment in the Pilbara region of Western Australia. The job roles assessed were project driller, mobile equipment operator, fixed plant maintainer, and drill and blast operator. The contaminants of interest were respirable crystalline silica, respirable dust, and inhalable dust. The novel approach of eliciting exposure estimates focusing on contaminant concentration and attribution of an exposure standard estimate was used. The majority of the elicited values were highly skewed; therefore, a scaled Beta distribution were fitted. These elicited fitted distributions were then compared to measured data distributions, the results of which had been collected as part of an occupational hygiene program assessing full-shift exposures to the same contaminants and job roles assessed by the experts. Our findings suggest that the participating experts within this study tended to overestimate exposures. In addition, the participating experts were more accurate at estimating percentage of an exposure standard than contaminant concentration. We demonstrate that this elicitation approach and the encoding methodology contained within can be applied to assess accuracy of exposure judgements which will impact on worker protection and occupational health outcomes.

Introduction

Accurate exposure judgments are the foundation of efficient and effective exposure management. The principal goal of the occupational hygiene professional is to protect all workers by reducing workplace health risks to as low as reasonably practicable. Of paramount importance is understanding worker exposure through direct measurement, but limited resources usually mean that hygienists need to apply a level of 'professional judgement', that is, the determination of whether an occupational exposure is acceptable based on limited information [1].

Qualitative exposure judgments based on subjective professional judgement form the foundation upon which most exposure assessments are based, and their accuracy is essential in ensuring appropriate risk management outcomes [2–4]. Professional judgement is considered a tool in the toolkit of the hygienist alongside the series of statistical parameters and analyses (i.e., sample size calculation, result aggregation, conformance assessment based on decision statistics) that are useful for describing exposure profiles in a quantitative fashion. However, the circumstances under which professional judgement is prescribed and understanding who can adequately dispense this expertise is still a topic for which ambiguity exists. Although the notion of professional judgement is generally accepted in the discipline of occupational hygiene, the definition is open to interpretation. Professional judgement may be exhibited through the application of knowledge, skills and experience in a way that is informed by professional standards, laws and ethical principles to develop an opinion or decision.

Any strategy where occupational hygienists make exposure judgments without adequate information or data has the potential to introduce inaccuracy and bias which could leave workers unprotected [1]. The process of making exposure judgments with inadequate information has sometimes been referred to as the 'art' of professional judgment. Expert elicitation is the process of retrieving and quantifying expert knowledge in a particular domain [5]. The use of expert elicitation helps to introduce a structure for validation to make the process more transparent and effective [1, 3, 4].

Accuracy of professional judgement

The application of professional judgement is an integral part of a hygienist's role and can determine whether resources applied to risk controls, respiratory protection, health surveillance and awareness programs effectively protect workers. Several studies have been published on the accuracy of professional judgment when completing exposure assessments in the field of occupational hygiene [6–11]. Some [3, 4, 12] involved a desktop assessment where qualitative task information and quantitative sampling data were provided while others relied on a walkthrough assessment where direct task observation was employed. The quantitative studies demonstrated that the accuracy of exposure judgments made by hygienists when monitoring data are available is low (<50% correct judgments) but still better than chance (25%) [3, 12]. A number of factors relating to experience, training, certification, and educational level were significant predictors of judgment accuracy [3, 12]. Findings from the walkthrough assessment approach where monitoring data were not available indicated the accuracy of exposure judgments made by hygienists (30% correct judgements) was not much different from chance (25%) [3, 12] and underestimation bias was also present.

Most exposure judgments made by hygienists are qualitative and can often be the determining factor as to whether any measurements should be made. Low accuracy of these judgments can therefore lead to incorrect follow-up activities, which may place workers at risk. Recent findings suggest that the understanding of how workplace factors affect exposure needs to be significantly improved among practitioners [7, 13] and that low accuracy in exposure assessment could be due to occupational hygienists receiving little formal training on how to conduct a basic exposure characterisation [14]. If this step of the exposure assessment is not conducted in a systematic way the hygienist may not investigate the exposure that presents the highest exposure potential with enough detail, leading to low judgment accuracy [14].

Cognitive biases and heuristics

A principal factor relating to the accuracy of professional judgement may be that of cognitive biases associated with the understanding of skewed lognormal distributions which are common in industrial hygiene data [3, 15]. When reviewing these distributions, mental shortcuts, known as heuristics, are often used which can lead to errors in judgment and introduce bias., There are three types of heuristics: availability, representativeness, and anchoring and adjustment [16, 17]. The availability heuristic reflects the tendency to equate the probability of an event with the ease with which an occurrence can be retrieved from our memory [16, 17]. For example, a hygienist may recall a family member or acquaintance who has suffered an asbestos-related disease, and thus may judge severity of asbestos exposure on the experiences of those around them. This may lead to a discounting of offsetting information, especially when such data conflict with easily recalled personal experience [18]. The degree to which a person's experiences and memory matches the true frequency determines whether these judgments are accurate. The representativeness heuristic reflects the assignment of an object or event to a specific group or class of events. If the decision maker lacks relevant experience, a surrogate (and less relevant) memory may be used, such as using a normal distribution rather than a skewed log-normal distribution. The anchoring and adjustment heuristic is a strategy for estimating uncertain quantities [16, 17]. When trying to determine the correct value, our minds 'anchor' on a value, and then adjust to accommodate additional information. The degree to which our final answer is anchored to the initial value can be influenced by many factors resulting in incorrect conclusions.

Despite these drawbacks, the use of expert knowledge in decision making has been gaining traction [19–21]. and have been shown to improve decision making across a broad range of disciplines, including psychology [8, 22], drug delivery and development [23], transdermal delivery and toxicity [24] environmental exposure assessment [25], habitats of rare species [26] and aggregate exposure assessment [27]. These approaches are particularly useful in areas where a traditional approach of using measured data may be problematic, such as occupational exposure assessment.

The main purpose of this study was to use expert elicitation to assess the professional judgement of a group of occupational hygienists ('experts') when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment. To achieve this, we assessed professional judgment accuracy by comparing expert judgements with quantitative exposure monitoring data.

Methods

An expert is commonly defined as someone with comprehensive and authoritative knowledge in an area not possessed by most people [28]. In the discipline of occupational hygiene in Australia, practitioners who attain the status of Certified Occupational Hygienist (COH) are recognised as experts in their field, and this was a prerequisite for participation in our study. The expert group consisted of four COHs, who all had working knowledge of the mining industry (currently employed in mining industry with a minimum of 15 years' experience working in a mining environment), the job roles, the contaminants of interest and the units and scales to be used in the elicitation process [29]. Notification of recruitment for the study was distributed through email with four of ten experts self-selecting into the study. Informed consent was obtained prior to participation. Two of the participating experts were located in Perth, Western Australia and two experts were located in Brisbane, Queensland. All four experts held a bachelor's degree, with three of the experts holding a master's degree and one holding a doctorate. All participating experts were male with the age range being 35–56 years. All data analysis was conducted by the authors in Perth, Western Australia.

Expert elicitation framework

One of the most important aspects of an elicitation protocol is the choice of summary statistics used to describe the distribution and the order in which these statistics are elicited [30–32]. These summary statistics need to be meaningful to the experts, especially when the experts have limited statistical and probability knowledge [33]. We created a protocol for elicitation which had the experts estimating point estimate values in the following sequence (i) lowest expected value (lowest value that would not surprise the expert), (ii) highest expected value (highest value that would not surprise the expert), and (iii) most common expected value (estimated most likely value that would lie between estimated 'lowest' and 'highest' values). The exact wording "most common" was employed to make certain that the elicited parameter matched to the model (mode of the distribution). The experts were asked to estimate both concentration and percentage of relevant occupational exposure limit (OEL). The elicitation steps, parameter descriptors, elicitation tool (Excel document) and relevant exposure limits were provided to the experts by email (refer to elicitation tool in the S1 Data).

Measured data

The measured data were collected in the form of full-shift, personal samples for the following job roles—project driller, mobile equipment operator, fixed plant maintainer, and drill and blast operator (Table 1). Locations for sampling included six iron ore mines located in the Pilbara region of Western Australia. The contaminants of interest were respirable crystalline silica, respirable dust, and inhalable dust. Personal samples were collected and analysed as per the applicable Australian Standard for each agent of interest, these being AS 2985–2009: *Workplace atmospheres–Method for sampling and gravimetric determination of respirable dust* and AS 3640–2009: *Workplace atmospheres–Method for sampling and gravimetric determination of inhalable dust*. Workers were selected randomly whenever possible using a random number table generated through the use of the RAND function in Excel. Equipment used to conduct the air sampling included an SKC AirChek 2000 pump with flexible tubing to 25mm diameter filters supported by a PVC cyclone or IOM sample head, depending on the agent to be measured. The designated flow rate for all samples collected was as per Australian Standards AS 2985:2009 (respirable fractions) and AS 3640:2009 (inhalable fractions) and was adjusted accurately using a calibrated flow meter (Defender 520 Model). All efforts were made to ensure calibration equipment and technique was of such accuracy that the flow rate was measured to within ±5%. Any samples that did not meet flow rate parameters were considered void and not used within the context of this study. Quantitative analysis of all air contaminant samples took place at MPL Laboratories (Perth, Western Australia), an environmental chemistry laboratory accredited for chemical testing with the National Association of Testing Authorities (NATA). Airborne samples for dust were analysed according to AS 2985:2009 for Respirable Dust and AS 3640:2009 for Inhalable Dust, which report the difference between the initial and final weight of the sample filter. Respirable crystalline silica was measured after ashing, redeposition and Fourier-transform infrared spectroscopy (FTIR) determination. Point estimate values of

Table 1. Personal samples (measured data) collected by contaminant for each job role.

Contaminant	Job role			
	Project driller	Mobile equipment operator	Fixed plant maintainer	Drill and blast operator
Respirable crystalline silica	$n = 220$	$n = 310$	$n = 200$	$n = 210$
Respirable dust	$n = 220$	$n = 310$	$n = 200$	$n = 210$
Inhalable dust	$n = 300$	$n = 350$	$n = 330$	$n = 280$

https://doi.org/10.1371/journal.pone.0269704.t001

(i) lowest, (ii) highest, and (iii) most common (mode) were calculated from the data set in order to define the true nature of the respective exposure profiles. Descriptive statistics for all measured data can be found in the S1 File.

Statistical encoding of elicitations

The majority of the elicited values were strongly left or right skewed, e.g., the most common value was equal to the minimum or maximum elicited value. A previous study showed that the scaled Beta distribution provided a better fit than the normal and lognormal distributions, particularly for strongly skewed data [30]. Therefore, for each expert, a scaled Beta distribution was fitted to each job role and contaminant combination by scaling the elicited values to the range [0, 1] [30]. A least squares approach was used to estimate the α and β parameters of the Beta distribution by ensuring that the distance between the elicited and encoded quantities was minimised using mean sum of squares (MSS) [30, 34, 35]. The expert's mode (most common) was defined as $(\alpha - 1)/(\alpha + \beta - 2)$. When the expert's lowest and most common estimate values were the same, then α was set to one and least squares was applied to identify β parameter [30]. Similarly, when the highest and most common estimate values were the same, then β was set to one and α was estimated using least squares. The function 'optim' in R [36] was employed to search across the parameter space to identify the best α and β parameters that minimise MSS [37]. To estimate a single distribution which captures the combined experts' values, we applied linear pooling by calculating the sum of the individual expert's distributions [21, 30].

The measured data were also encoded into scaled Beta distributions. The mode and the lower and upper bounds for the 95% confidence interval were calculated for each job role and contaminant measured data combination. These summary statistic values were then encoded into scaled Beta distributions using the same methodology as the elicited values.

Results

The participating experts reported a timeframe of between 45–60 minutes to complete all elicitations (all job roles, all contaminants), and all experts expressed confidence that the process captured their knowledge of exposure. Figs 1–3 show the individual and combined expert plausible (density) estimates of exposure concentration (mg/m^3) compared with the measured data across the four job roles with respect to each contaminant and Figs 4–6 show values in percentage of the relevant OEL. The term 'plausibility' can be defined as the degree of expert support on the estimates of exposure concentration and OEL estimates [30]. Most measured data follow a lognormal distribution, exhibiting right (positive) skewness [38], and this is observed in 60% of the measured data distributions (all Figs except 2 and 5). Within all Figs, the experts are denoted in the colours blue, red, black and green. The combined expert's distribution is denoted with a dashed line and measured data is presented as a purple line.

Comparison of the most common exposure value between the experts and the measured data demonstrate that all experts provided a value higher than the measured value for all contaminants and all job roles, meaning exposure has been overestimated for both percentage of the OEL and concentration in all elicitations. For the highest exposure value, the experts overestimated exposure 41% and 54% of the time respectively for OEL and concentration. For the lowest exposure values experts overestimated exposure 96% of the time for both OEL and concentration when compared with the measured data.

For inhalable dust concentration, all four experts were similar to the measured data distributions for the job roles of fixed plant maintainer and mobile equipment operator (Fig 1).

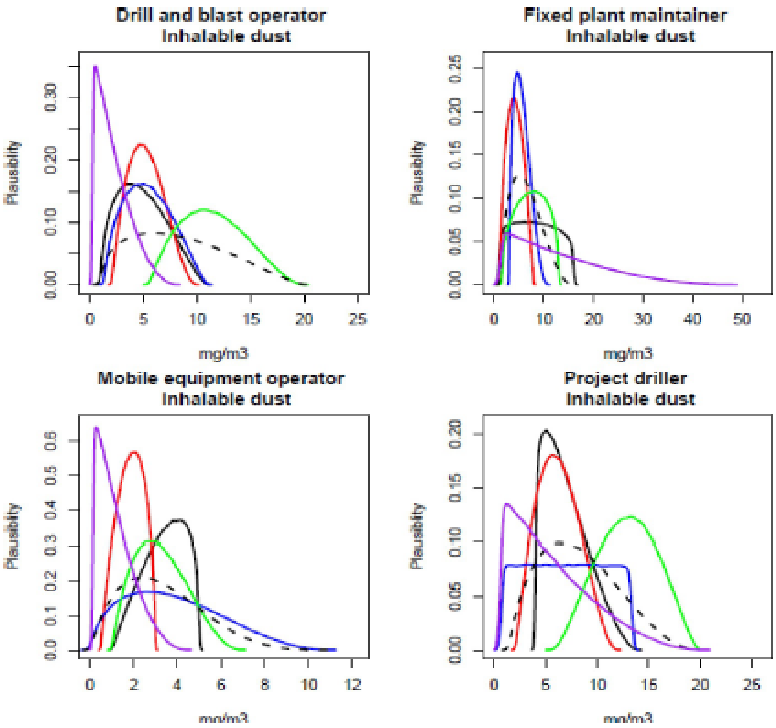

Fig 1. Expert estimates and measured data of inhalable dust concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

https://doi.org/10.1371/journal.pone.0269704.g001

However, for the other two roles, the green expert estimated higher values than the other experts and the measured data.

For all four respirable crystalline silica plots, the measured data had very tight distributions (Fig 2). The blue expert's distribution was very wide compared to measured data and all other experts' distributions. For the job role drill and blast operator, all expert's most common values were higher than the measured distribution. For fixed plant maintainer, the blue expert was lower and most common values agreed with the measured data; however, the other three (black, red and green) expert's lower and most common values were higher than the measured data.

For respirable dust concentration, no expert agreed with the measured data, and the range of blue and green experts' distribution was similar (Fig 3). The green expert's distribution was very different to the measured data and all other experts' distributions for the job role project driller.

For the estimates of the percent of the inhalable dust OEL, all expert distributions fell within the range of the measured data (Fig 4). In addition, all expert distributions were similar to the measured data for the job role of fixed plant maintainer. For the other job roles, the modes (most common value) of the expert distributions were higher than the measured data. All estimates of the most common value were similar to the measured data for the job role of project

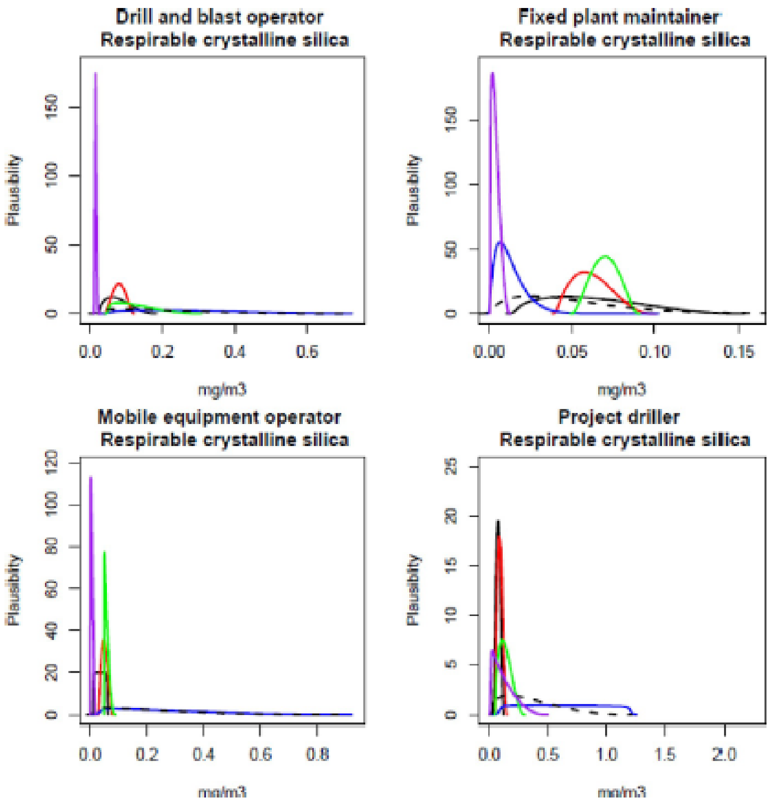

Fig 2. Expert estimates and measured data of respirable crystalline silica concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

https://doi.org/10.1371/journal.pone.0269704.g002

driller when assessing the percent of the OEL for respirable crystalline silica (Fig 5). For the other three job roles, the blue expert distribution had a wide range when compared to the measured data and other experts.

For the assessment of the percent of the respirable dust OEL, the measured data distribution were right skewed except for the job role of mobile equipment operator (Fig 6). The green expert's distributions disagreed with the measured data in all four job roles. All lowest elicited values were in the range of the measured data. For drill and blast operator, all experts had a similar distribution compared with the measured distribution, however the most common value of all the experts was slightly higher compared to the mode of the measured data.

Discussion

The main purpose of this study was to use expert elicitation to assess the professional judgement of a group of occupational hygienists. We have presented and evaluated a statistical methodology for the encoding of elicited information into distributions from multiple experts. We applied a scaled Beta distribution to expert and measured data; this approach was able to

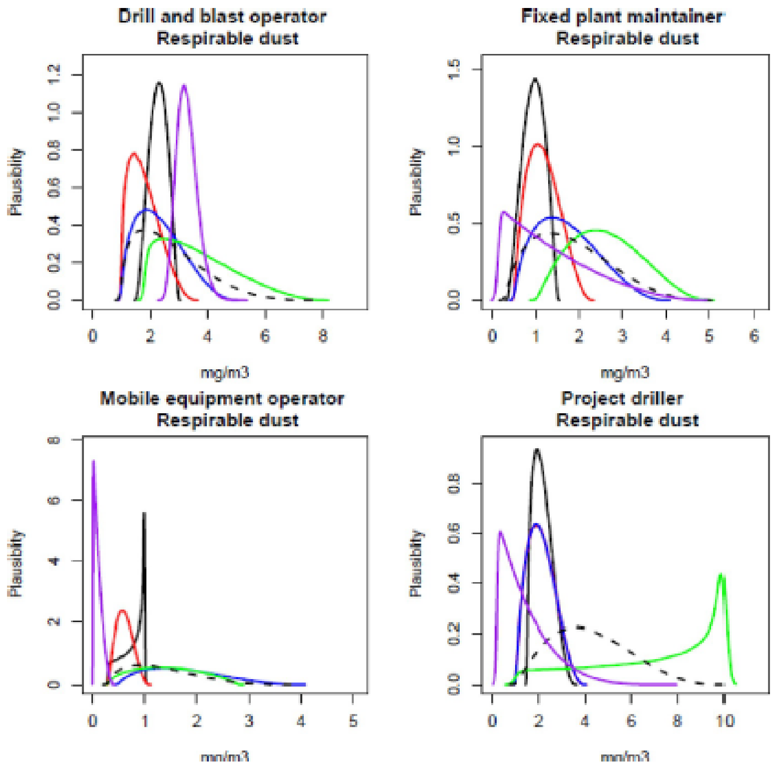

Fig 3. Expert estimates and measured data of respirable dust concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

https://doi.org/10.1371/journal.pone.0269704.g003

accommodate both left and right skewed distributions as well as "normal" distributions. Our findings suggest that the participating occupational hygienists within this study were inclined to overestimate exposures and that they were more accurate at estimating percentage of OEL than concentration values (refer to study comparison tables in the S2 Data). Our approach differs from previous research in the way in which exposure assumptions were elicited, by focusing on contaminant concentration and attribution of an exposure standard percentage estimate.

The use of expert knowledge in decision making has been gaining traction in many scientific disciplines, most notably in areas where a traditional approach of utilising observed data may not be a practical option [19–21]. Most assessments conducted within a comprehensive exposure assessment program are qualitative, that is, completed without measured data. This approach is by design and is practically necessary, as the number of exposure scenarios in a workplace may total in the hundreds in which conducting quantitative exposure assessments (i.e., using measured data with sufficient samples to support decision making) for every scenario is not feasible [2]. For example, the American Industrial Hygiene Association (AIHA)

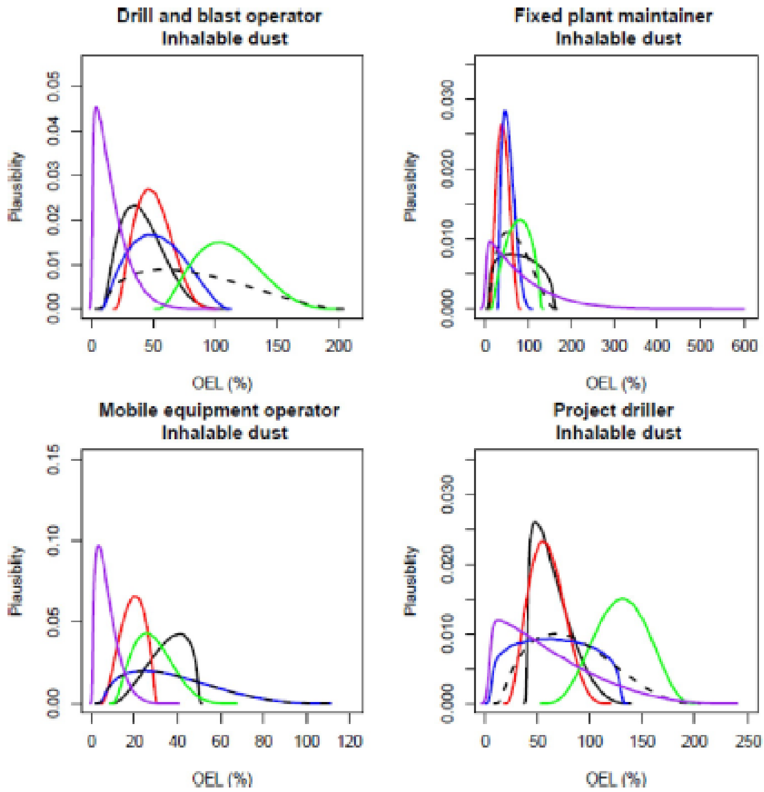

Fig 4. Expert estimates and measured data of inhalable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

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exposure assessment strategy calls for initial, qualitative assessments of exposures, relative to a reference exposure level [15].

Occupational hygienists review the workforce, materials, exposure agents, tasks, equipment, exposure controls and identify exposure groups that will be assessed and controlled depending on the final judgments. The exposure evaluation for any job role requires the selection of an OEL and a judgment by the hygienist about where the decision statistic (for example, the 95th percentile of the exposure distribution for the job role) falls in relation to the OEL [15]. Professional judgement is considered a 'tool in the toolkit' of the hygienist and serves as a key factor when making a determination on whether an exposure is acceptable in the context of an occupational environment. However, for the most part, subjective qualitative judgments in the field of occupational hygiene have proven to be no more accurate than random chance. This may be because patterns of exposures in many workplaces have a significant degree of uncertainty and unpredictability and there may be little or no data available on these exposure levels. Such situations have been defined as 'low-validity' environments [22] and perhaps somewhat

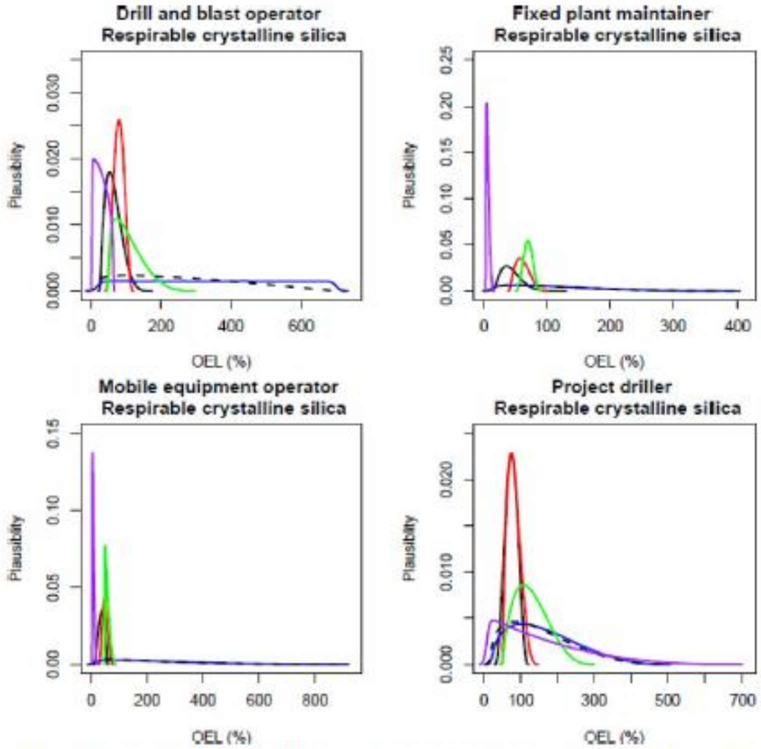

Fig 5. Expert estimates and measured data of respirable crystalline silica percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

https://doi.org/10.1371/journal.pone.0269704.g005

paradoxically, judgement decisions have been shown to be most accurate in these highly uncertain situations, particularly when paired with checklists or models. The use of a checklist that considers consistent inputs is shown to be more reliable at arriving at a judgement than a purely 'human' focussed way but this has not previously been assessed in the occupational hygiene setting [4, 12, 22].

A key observation from this study is the experts' proclivity to consistently overestimate exposures. This appears to be a point of difference when compared to similar studies where there was a significant underestimation bias in the exposure judgments when the range is examined [3, 4, 12]. The reasons behind this finding are worth exploring. In other expert elicitation studies [19–21] experts are typically able to estimate the range of measured data distribution quite accurately, however the most common value tends to be higher than the measured value. Our study found that the most common exposure value between the experts and the measured data was higher than the measured value for all contaminants and all job roles for both percentage of the OEL and concentration in all elicitations. We found that the experts lowest exposure value was nearly always (96% of the time) higher than that of the measured equivalent and the highest exposure value was overestimated about half of the time (41%

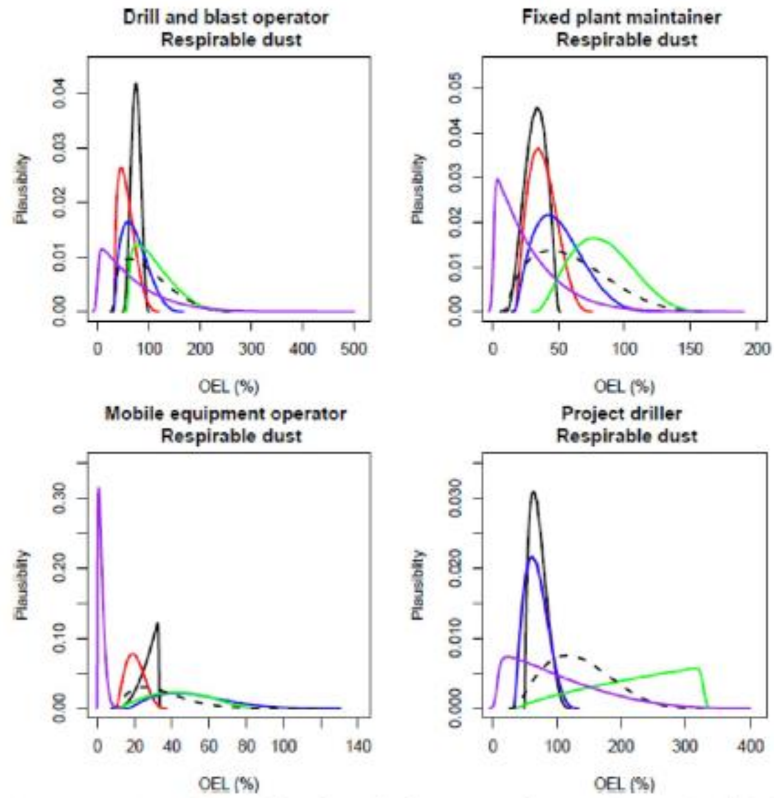

Fig 6. Expert estimates and measured data of respirable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

https://doi.org/10.1371/journal.pone.0269704.g006

and 54% of the time for percentage of OEL and concentration respectively). These findings suggest that hygienists may be more concerned about the upper bound of an exposure profile as opposed to the lower and therefore concentrated more on estimating this more carefully.

Comparing the expert versus the measured data distributions show that the experts appear to be able to estimate percentage of the OEL more accurately than concentration. This may be attributable to a variety of factors, including risk communication. Given one of the mandates of the occupational hygienist is to 'distil' complex data into easy-to-understand messages for a workforce, many hygienists have taken to expressing results of monitoring data as percentages of the applicable exposure standard and so this way to present data is likely to be more familiar to them.

With respect to the experts, the green expert was notably divergent from the measured data and their elicitations often yielded different results from the other experts. This disparity warrants further investigation into how the green expert executed the elicitations, and whether any cognitive biases attributable to the heuristics of availability, representativeness, and anchoring and adjustment were present during this exercise. A deeper dive into the determinants of the elicited values would provide transparency around the decision-making practices of each expert.

A strength of the study was the statistical encoding of both expert and measured data into scaled Beta distributions. The advantage of the scaled Beta distribution when compared with the normal and lognormal distributions is that it performs better over all levels of skewness, in particular providing accurate encoded values under extreme skewness [30]. This is particularly useful when the skewness is expected to be high, or in situations where the degree of uncertainty is high. Both situations are present within the context of this study, and this illustrates why probabilistic methods are attractive to hygienists who are required to make exposure judgments with limited sampling data [39].

A further strength of this study was that we had a large amount of measured data to use for comparison against the expert elicitations. A standard approach to exposure assessment in the field of occupational hygiene dictates randomly sampling 6–10 events of a specific job role and calculating an upper tail decision statistic such as the 95th percentile with an upper confidence limit (e.g. 90th or 95th) [15]. This approach to exposure assessment has been utilised in the field for many years and was based on the assumption of a stable and predictable work environment wherein a reliable mean and geometric standard deviation can be calculated after 6–10 samples [15]. With the advent of a more dynamic workforce expected to complete multiple tasks across different work environments (as is the case in the mining industry), the concept of full-shift personal monitoring to define the exposure profile of a job role or similar exposure group (SEG) may not be an optimal approach. Given this, the large dataset in this study was useful in capturing the real distribution of the measured data that may be present in a dynamic work environment [40]. With the introduction of sensor measurement technology (sometimes referred to as 'real-time' monitoring) future studies may focus on comparisons between experts and quantitative measurements that are task or source based, which may present a more accurate picture of a worker's exposure in a dynamic occupational environment.

A potential limitation of this study was the number of experts recruited for elicitation. Although there is no absolute guideline on which to base the number of experts invited to provide input, a panel of expert elicitation practitioners determined that at least six experts should be included to ensure robustness of results [41]. The same panel also concluded that a point of diminishing returns was reached beyond twelve experts. Future studies may wish to expand the number of experts involved to further broaden the range of experiences that contribute to a person's professional judgement. However, a challenge to these further studies is the availability of both general and industry-specific experts. In addition, the study was completed in the context of a mining environment with only three agents of interest, all of which were particulates. Future studies should ensure a larger sample size of experts are recruited and assessment be focused to a larger suite of airborne contaminants across other industries.

Another limitation of the study are the uncontrolled conditions that the expert elicitations were completed. The elicitation steps, parameter descriptors, elicitation tool (Excel document) and relevant exposure limits were provided to the experts by email; however, the authors were not aware, and did not specifically enquire, as to any additional resources or information used by the experts when completing their judgements. In addition, a 'hard' timeframe for return of the elicitation tool with completed judgements was not set by the authors, rather a 'request' was made to return the completed protocol document within a two-week period. Further studies should ensure that any additional resources or information utilised during the elicitation process are categorised and reported. Given the role of a practicing hygienist, it may be impractical to expect elicitations be completed under controlled conditions (i.e., in a supervised exam room), however specifying a set timeframe for completion of the elicitation protocol should also be considered.

Conclusions

The results in this study suggest that, in the absence of measured data and under the same methodology described within this paper, the participating occupational hygienists tended toward an overestimation of exposures. The practical implication of overestimating may be an 'overprotection' of workgroups, or a misallocation of resources such as risk controls, respiratory protection, health surveillance and awareness programs. Conversely, the consequences of underestimating exposure (as has been reported in other studies) may leave workers unprotected.

From a practitioner standpoint, hygienists would err toward a more conservative approach to protecting worker health if given the choice; however, there are pros and cons to this. For example, a conservative approach may result in higher order respiratory protection being prescribed in the absence of actual risk, which may impact adversely on an individual's metabolic load. In a high heat environment, the result of this could be dangerous to the individual through the development of a heat-related illness. Similarly, overestimation may result in scant resources not being adequately apportioned based on risk, which could extend out to critical health surveillance (i.e., disease identification) services.

Despite these findings, it is clear that the field of occupational hygiene is integral to the global effort of protecting worker health. The elicitation protocol used in this study, although reflective of 'real world' challenges of assessing exposures in the absence of measured data, was designed to require a high degree of specificity when the experts were making their respective judgements. The concept of exposure assessment is complex, with the amount of information required to be assessed often exceeding the capacity of the pre-frontal cortex, the decision-making area of the brain [2, 42]. This overload can make the brain vulnerable to flaws of memory and distraction, which can lead to bias and over-confidence in decision-making [2, 42].

These findings suggest that improved accuracy in exposure assessment in the absence of measured data is needed, particularly in the context of a dynamic work environment where job roles are expected to complete tasks across different work fronts, as is the case within an Australian mining context. Further efforts should assess the expert's decision-making process and the determinants of their judgements. Future research should focus on these determinants of professional judgement to better assess accuracy and inform formalised training programmes, models, and other tools to improve exposure assessment within the discipline of occupational hygiene.

Supporting information

S1 Data.
(XLSX)

S2 Data.
(XLSX)

S1 File.
(DOCX)

Acknowledgments

We thank the occupational hygienists who participated in this study by contributing their expert judgements.

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Writing – original draft: David Michael Lowry.

Writing – review & editing: David Michael Lowry, Lin Fritschi, Rebecca A. O'Leary.

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Appendix I: Published paper 2b (Chapter 5)

ScienceDirect

Safety and Health at Work
Volume 13, Supplement, January 2022, Pages S137-S138

10. INDUSTRIAL HYGIENE

Assessment of professional judgement in the field of occupational hygiene: comparison of expert and observed data distributions

David Lowry [1], Lin Fritschi [2], Ben Mullins [2], Rebecca O'Leary [3]

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The concept of professional judgement underpins the way in which an occupational hygienist assesses an exposure problem. Despite the importance placed on professional judgement in the discipline, a method of assessment to characterise accuracy has not been available. In this paper, we assess the professional judgement of a group of occupational hygienists ('experts') when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment. The novel approach of eliciting exposure assumptions focusing on contaminant concentration and attribution of an exposure standard estimate was used. These elicited values were then compared to measured data using a scaled Beta distribution, providing a good approximation of the expert's professional judgement in the context of the study. Our findings suggest that occupational hygienists are inclined to overestimate exposures and that they were more accurate at estimating percentage of exposure standard than the actual concentration values. The practical implication of overestimating may be an 'overprotection' of workgroups, or a misallocation of resources such as risk controls, respiratory protection, health surveillance and awareness programs. We demonstrate

that this approach and the encoding methodology contained within can be applied to assess accuracy of exposure judgements which will impact on worker protection and occupational health outcomes.

Special issue articles   Recommended articles

Cited by (0)

Appendix J: Descriptive statistics from measured data – published paper 2 (Chapter 5)

Drill & Blast Operator, Respirable Crystalline Silica

DESCRIPTIVE STATISTICS	
Maximum (max)	118.73
Minimum (min)	2.64
Range	116
Percent above OEL (%>OEL)	0.0
Mean	12
Median	8
Standard deviation (s)	13
Mean of log transformed data (LN)	2.18
Std. deviation of log transformed data(LN)	0.596
Geometric mean (GM)	8.9
Geometric standard deviation (GSD)	1.81

Project Driller, Respirable Crystalline Silica

DESCRIPTIVE STATISTICS	
Maximum (max)	690.84998
Minimum (min)	3.52
Range	687
Percent above OEL (%>OEL)	8.2
Mean	45
Median	16
Standard deviation (s)	105
Mean of log transformed data (LN)	2.91
Std. deviation of log transformed data(LN)	1.195
Geometric mean (GM)	18.3
Geometric standard deviation (GSD)	3.30

Mobile Equipment Operator, Respirable Crystalline Silica

DESCRIPTIVE STATISTICS	
Maximum (max)	23.25
Minimum (min)	2.64
Range	21
Percent above OEL (%>OEL)	0.0
Mean	7
Median	6
Standard deviation (s)	4
Mean of log transformed data (LN)	1.84
Std. deviation of log transformed data(LN)	0.331
Geometric mean (GM)	6.3
Geometric standard deviation (GSD)	1.39

Fixed Plant Maintainer, Respirable Crystalline Silica

DESCRIPTIVE STATISTICS	
Maximum (max)	20.969999
Minimum (min)	2.99
Range	18
Percent above OEL (%>OEL)	0.0
Mean	7
Median	6
Standard deviation (s)	3
Mean of log transformed data (LN)	1.81
Std. deviation of log transformed data(LN)	0.287
Geometric mean (GM)	6.1
Geometric standard deviation (GSD)	1.33

Project Driller, Inhalable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	235.52
Minimum (min)	3.48
Range	232
Percent above OEL (%>OEL)	5.0
Mean	25
Median	12
Standard deviation (s)	50
Mean of log transformed data (LN)	2.56
Std. deviation of log transformed data(LN)	0.919
Geometric mean (GM)	12.9
Geometric standard deviation (GSD)	2.51

Mobile Equipment Operator, Inhalable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	84.629997
Minimum (min)	0.19
Range	84
Percent above OEL (%>OEL)	0.0
Mean	8
Median	4
Standard deviation (s)	13
Mean of log transformed data (LN)	1.30
Std. deviation of log transformed data(LN)	1.126
Geometric mean (GM)	3.7
Geometric standard deviation (GSD)	3.08

Fixed Plant Maintainer, Inhalable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	675.77002
Minimum (min)	0.41
Range	675
Percent above OEL (%>OEL)	3.4
Mean	37
Median	9
Standard deviation (s)	74
Mean of log transformed data (LN)	2.45
Std. deviation of log transformed data(LN)	1.293
Geometric mean (GM)	11.6
Geometric standard deviation (GSD)	3.64

Drill & Blast Operator, Inhalable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	352.17001
Minimum (min)	0.51
Range	352
Percent above OEL (%>OEL)	2.1
Mean	28
Median	13
Standard deviation (s)	55
Mean of log transformed data (LN)	2.48
Std. deviation of log transformed data(LN)	1.120
Geometric mean (GM)	12.0
Geometric standard deviation (GSD)	3.06

Project Driller, Respirable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	395.39999
Minimum (min)	2.67
Range	393
Percent above OEL (%>OEL)	2.2
Mean	23
Median	10
Standard deviation (s)	58
Mean of log transformed data (LN)	2.45
Std. deviation of log transformed data(LN)	0.942
Geometric mean (GM)	11.6
Geometric standard deviation (GSD)	2.57

Mobile Equipment Operator, Respirable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	68.889999
Minimum (min)	0.22
Range	69
Percent above OEL (%>OEL)	0.0
Mean	7
Median	4
Standard deviation (s)	10
Mean of log transformed data (LN)	1.34
Std. deviation of log transformed data(LN)	0.834
Geometric mean (GM)	3.8
Geometric standard deviation (GSD)	2.30

Fixed Plant Maintainer, Respirable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	225.92
Minimum (min)	0.32
Range	226
Percent above OEL (%>OEL)	1.6
Mean	23
Median	15
Standard deviation (s)	28
Mean of log transformed data (LN)	2.46
Std. deviation of log transformed data(LN)	1.208
Geometric mean (GM)	11.7
Geometric standard deviation (GSD)	3.35

Drill & Blast Operator, Respirable Dust

DESCRIPTIVE STATISTICS	
Maximum (max)	98.470001
Minimum (min)	0.02
Range	98
Percent above OEL (%>OEL)	0.0
Mean	13
Median	11
Standard deviation (s)	14
Mean of log transformed data (LN)	2.13
Std. deviation of log transformed data(LN)	1.141
Geometric mean (GM)	8.4
Geometric standard deviation (GSD)	3.13

Appendix K: Elicitation instructions and tool – published paper 2 (Chapter 5)

Elicitation steps	Elicitation parameter descriptors
1. Review elicitation table on the following tab 2. Work through the elicitation table by placing your best estimation* for each exposure value in the corresponding field 3. Values are required to be given by measurement concentration <u>and</u> percentage of the occupational exposure limit (OEL) ***this should be based on your expert opinion and professional judgement***	**Lowest:** Lowest exposure value (value the expert would be really surprised if it was less than) **Highest:** Highest exposure value (value the expert would be really surprised if it was more than) **Most common:** Most common exposure value (estimated most likely value that would lie between estimated 'lowest' and 'highest' values)
Relevent occupatinal exposure limits (OELs) (for an 8 hour work shift)	**Job role descriptors**
Respirable crystalline silica: 0.1 mg/m3 **Inhalable dust:** 10 mg/m3 **Respirable dust:** 3 mg/m3	**Project driller:** All staff involved in exploration drilling. **Mobile equipment operator:** All occupations that operate heavy equipment including, but not limited to, haul truck drivers, excavators, grader, and loader operators, rubber wheel dozer and track dozer operators. **Fixed plant maintainer:** Process plant maintainers, other than those working in workshops. **Drill and blast operator:** All staff involved in blasting operations.

[redacted]		**Job role**							
Contaminant	**Elicitation value**	Project driller		Mobile equipment operator		Fixed plant maintainer		Drill and blast operator	
		%OEL	mg/m3	%OEL	mg/m3	%OEL	mg/m3	%OEL	mg/m3
Respirable crystalline silica	Lowest								
	Highest								
	Most common								
Inhalable dust	Lowest								
	Highest								
	Most common								
Respirable dust	Lowest								
	Highest								
	Most common								

Appendix L: AIOH 2021 Conference proceedings excerpt – published paper 2 (Chapter 5)

USE OF EXPERT ELICITATION IN THE FIELD OF OCCUPATIONAL HYGIENE: COMPARISON OF EXPERT AND OBSERVED DATA DISTRIBUTIONS

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Abstract

The concept of professional judgement underpins the way in which an occupational hygienist assesses an exposure problem. Despite the importance placed on professional judgement in the discipline, a method of assessment to characterise accuracy has not been available. In this paper, we assess the professional judgement of a group of occupational hygienists ('experts') when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment. The novel approach of eliciting exposure estimates focusing on contaminant concentration and attribution of an exposure standard estimate was used. The majority of the elicited values were highly skewed; therefore, a scaled Beta distribution were fitted. These elicited fitted distributions were then compared to measured data distributions. We demonstrate that this elicitation approach and the encoding methodology contained within can be applied to assess accuracy of exposure judgements which will impact on worker protection and occupational health outcomes.

1. Introduction

Accurate exposure judgments are the foundation of efficient and effective exposure management. The principal goal of the occupational hygiene professional is to protect all workers by reducing workplace health risks to as low as reasonably practicable. Of paramount importance is understanding worker exposure through direct measurement, but limited resources usually mean that hygienists need to apply a level of 'professional judgement', that is, the determination of whether an occupational exposure is acceptable based on limited information (1). Professional judgement is considered a tool in the toolkit of the hygienist alongside the series of statistical parameters and analyses (i.e., sample size calculation, result aggregation, conformance assessment based on decision statistics) that are useful for describing exposure profiles in a quantitative fashion. However, the circumstances under which professional judgement is prescribed and understanding who can adequately dispense this expertise is still a topic for which ambiguity exists. Although the notion of professional judgement is generally accepted in the discipline of occupational hygiene, the definition is open to interpretation. Professional judgement may be exhibited through the application of knowledge, skills and experience in a way that is informed by professional standards, laws and ethical principles to develop an opinion or decision and is assumed when an individual is a practicing hygienist who is certified by an applicable institute or organisation.

Any strategy where occupational hygienists make exposure judgments without adequate information or data has the potential to introduce inaccuracy and bias which could leave workers unprotected (1). The process of making exposure judgments with inadequate information has sometimes been referred to as the 'art' of professional judgment. Expert elicitation is the process of retrieving and quantifying expert knowledge in a particular domain (2). The use of expert elicitation helps to introduce a structure for validation to make the process more transparent and effective (1, 3, 4).

Accuracy of professional judgement

The application of professional judgement is an integral part of a hygienist's role and can determine whether resources applied to risk controls, respiratory protection, health surveillance and awareness programs effectively protect workers. Several studies have been published on the accuracy of professional judgment in occupational hygiene (5-10). Some (3, 4, 11) involved a desktop assessment where qualitative task information and quantitative sampling data were provided while others relied on a walkthrough assessment where direct task observation was employed. The quantitative studies demonstrated that the accuracy of exposure judgments made by hygienists when monitoring data are available is low (<50% correct judgments) but still better than chance (25%) (3, 11). A number of factors relating to experience, training, certification, and educational level were significant predictors of judgment accuracy (3, 11). Findings from the walkthrough assessment approach where monitoring data were not available indicated the accuracy of exposure judgments made by hygienists (30% correct judgements) was not much different from chance (25%) (3, 11) and underestimation bias was also present.

Most exposure judgments made by hygienists are qualitative and can often be the determining factor as to whether any measurements should be made. Low accuracy of these judgments can therefore lead to incorrect follow-up activities, which may place workers at risk. Recent findings suggest that the understanding of how workplace factors affect exposure needs to be significantly improved among practitioners (6, 12) and that low accuracy in exposure assessment could be due to occupational hygienists receiving little formal training on how to conduct a basic exposure characterisation (13). If this step of the exposure assessment is not conducted in a systematic way the hygienist may not investigate the exposure that presents the highest exposure potential with enough detail, leading to low judgment accuracy (13).

1.2 Cognitive biases and heuristics

A principal factor relating to the accuracy of professional judgement may be that of cognitive biases associated with the understanding of skewed lognormal distributions which are common in industrial hygiene data (3). (14). When reviewing these distributions, mental shortcuts, known as heuristics, are often used which can lead to errors in judgment and introduce bias., There are three types of heuristics: availability, representativeness, and anchoring and adjustment (15, 16). The availability heuristic reflects the tendency to equate the probability of an event with the ease with which an occurrence can be retrieved from our memory (15, 16). The degree to which a person's experiences and memory matches the true frequency determines whether these judgments are accurate. The representativeness heuristic reflects the assignment of an object or event to a specific group or class of events. If the decision maker lacks relevant experience, a surrogate (and less relevant) memory may be used, such as using a normal distribution rather than a skewed log-normal distribution. The anchoring and adjustment heuristic is a strategy for estimating uncertain quantities (15, 16). When trying to determine the correct value, our minds 'anchor' on a value, and then adjust to accommodate additional information. The degree to which our final answer is anchored to the initial value can be influenced by many factors resulting in incorrect conclusions.

Despite these drawbacks, the use of expert knowledge in decision making has been gaining traction (17-19). and have been shown to improve decision making across a broad range of disciplines, including psychology (7, 20), drug delivery and development (21), transdermal delivery and toxicity (22) environmental exposure assessment (23), habitats of rare species (24) and aggregate exposure assessment (25). These approaches are particularly useful in areas where a traditional approach of using measured data may be problematic, such as occupational exposure assessment.

The main purpose of this study was to use expert elicitation to assess the professional judgement of a group of occupational hygienists ('experts') when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment. To achieve this, we assessed professional judgment accuracy by comparing expert judgements with quantitative exposure monitoring data.

2. Methods

An expert is commonly defined as someone with comprehensive and authoritative knowledge in an area not possessed by most people (26). In the discipline of occupational hygiene in Australia, practitioners who attain the status of Certified Occupational Hygienist (COH) are recognised as experts in their field, and this was a prerequisite for participation in our study. The expert group consisted of four COHs, who all had working knowledge of the mining industry, the job roles, the contaminants of interest and the units and scales to be used in the elicitation process (27).

Expert elicitation framework

One of the most important aspects of an elicitation protocol is the choice of summary statistics used to describe the distribution and the order in which these statistics are elicited (28-30). These summary statistics need to be meaningful to the experts, especially when the experts have limited statistical and probability knowledge (31). We created a protocol for elicitation which had the experts estimating point estimate values in the following sequence (i) lowest (value the expert would be really surprised if it was less than the measured value), (ii) highest (value the expert would be really surprised if it was more than the measured value), and (iii) most common (estimated most likely value that would lie between estimated 'lowest' and 'highest' values). The exact wording "most common" was employed to make certain that the elicited parameter matched to the model (mode of the distribution). The experts were asked to estimate both concentration and percentage of relevant occupational exposure limit (OEL). The elicitation steps, parameter descriptors, elicitation tool (Excel document) and relevant exposure limits were provided to the experts by email.

Measured data

The measured data were collected in the form of full-shift, personal samples for the following job roles - project driller, mobile equipment operator, fixed plant maintainer, and drill and blast operator (Table 1). The contaminants of interest were respirable crystalline silica, respirable dust, and inhalable dust. Personal samples were collected and analysed as per the applicable Australian Standard for each agent of interest. Workers were selected randomly whenever possible using a random number table. Equipment used to conduct the air sampling included an SKC AirChek 2000 pump with flexible tubing to 25mm diameter filters supported by a PVC cyclone or IOM sample head, depending on the agent to be measured. The designated flow rate for all samples collected was as per Australian Standard and was adjusted accurately using a calibrated flow meter (Defender 520 Model). All efforts were made to ensure calibration equipment and technique was of such accuracy that the flow rate was measured to within ±5%. Any samples that did not meet flow rate parameters were considered void and not used within the context of this study. Quantitative analysis of all air contaminant samples took place at MPL Laboratories (Perth, Western Australia), an environmental chemistry laboratory accredited for chemical testing with the National Association of Testing Authorities (NATA). Airborne samples for dust were analysed according to AS 2985 for Respirable Dust and AS 3640 for Inhalable Dust, which report the difference between the initial and final weight of the sample filter. Respirable crystalline silica was measured after ashing, redeposition and Fourier-transform infrared spectroscopy (FTIR) determination. Point estimate values of (i) lowest, (ii) highest, and (iii) most common (mode) were calculated from the data set in order to define the true nature of the respective exposure profiles.

Table 1. Personal samples (measured data) collected by contaminant for each job role

Contaminant	Job role			
	Project driller	Mobile equipment operator	Fixed plant maintainer	Drill and blast operator
Respirable crystalline silica	*n* = 220	*n* = 310	*n* = 200	*n* = 210
Respirable dust	*n* = 220	*n* = 310	*n* = 200	*n* = 210
Inhalable dust	*n* = 300	*n* = 350	*n* = 330	*n* = 280

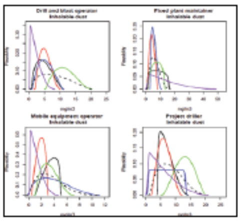
Statistical encoding of elicitations

The majority of the elicited values were strongly left or right skewed, e.g., the most common value was equal to the minimum or maximum elicited value. A previous study showed that the scaled Beta distribution provided a better fit than the normal and lognormal distributions, particularly for strongly skewed data (28). Therefore, for each expert, a scaled Beta distribution was fitted to each job role and contaminant combination by scaling the elicited values to the range [0, 1] (28). A least squares approach was used to estimate the α and β parameters of the Beta distribution by ensuring that the distance between the elicited and encoded quantities was minimised using mean sum of squares (MSS) (28, 32, 33). The expert's mode (most common) was defined as $(\alpha - 1)/(\alpha + \beta - 2)$. When the expert's lowest and most common estimate values were the same, then α was set to one and least squares was applied to identify β parameter (28). Similarly, when the highest and most common estimate values were the same, then β was set to one and α was estimated using least squares. The function 'optim' in R (34) was employed to search across the parameter space to identify the best α and β parameters that minimise MSS (35). To estimate a single distribution which captures the combined experts' values, we applied linear pooling by calculating the sum of the individual expert's distributions (19, 28).The measured data were also encoded into scaled Beta distributions. The mode and the lower and upper bounds for the 95% confidence interval were calculated for each job role and contaminant measured data combination. These summary statistic values were then encoded into scaled Beta distributions using the same methodology as the elicited values.

3. Results

Each elicitation took approximately 45-60 minutes to complete, and all experts expressed confidence that the process captured their knowledge of exposure. Figures 1–3 show the individual and combined expert estimates of exposure concentration (mg/m^3) compared with the measured data across the four job roles with respect to each contaminant and Figures 4-6 show values in percentage of the relevant OEL. Most measured data follow a lognormal distribution, exhibiting right (positive) skewness (36), and this is observed in 60% of the measured data distributions (all Figures except 2 and 5).

Comparison of the most common exposure value between the experts and the measured data demonstrate that all experts provided a value higher than the measured value for all contaminants and all job roles, meaning exposure has been overestimated (in some cases, significantly) for both percentage of the OEL and concentration in all elicitations. For the highest exposure value, the experts overestimated exposure 41% and 54% of the time respectively for OEL and concentration. For the lowest exposure values experts overestimated exposure 96% of the time for both OEL and concentration when compared with the measured data.



For inhalable dust concentration, all four experts were similar to the measured data distributions for the job roles of fixed plant maintainer and mobile equipment operator (Figure 1). However, for the other two roles, the green expert estimated higher values than the other experts and the measured data.

Figure 1. Expert estimates and measured data of inhalable dust concentrations. Each curve depicts the experts support (probability density), or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black, and green; combined experts are the dashed line. Measured data is presented as purple.

For all four respirable crystalline silica plots, the measured data had very tight distributions (Figure 2). The blue expert's distribution was very wide compared to measured data and all other experts' distributions. For the job role drill and blast operator, all expert's most common values were higher than the measured distribution. For fixed plant maintainer, the blue expert was lower and most common values agreed with the measured data; however, the other three (black, red, and green) expert's lower and most common values were higher than the measured data.

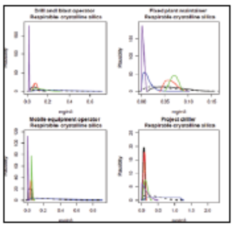


Figure 2. Expert estimates and measured data of respirable crystalline silica concentrations. Each curve depicts the experts support (probability density), or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black, and green; combined experts are the dashed line. Measured data is presented as purple.

For respirable dust concentration, no expert agreed with the measured data, and the range of blue and green experts' distribution was similar (Figure 3). The green expert's distribution was very different to the measured data and all other experts' distributions for the job role project driller.

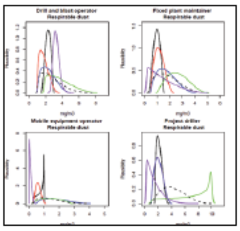


Figure 3. Expert estimates and measured data of respirable dust concentrations. Each curve depicts the experts support (probability density), or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black, and green; combined experts are the dashed line. Measured data is presented as purple.

For the estimates of the percent of the inhalable dust OEL, all expert distributions fell within the range of the measured data (Figure 4). In addition, all expert distributions were similar to the measured data for the job role of fixed plant maintainer. For the other job roles, the modes (most common value) of the expert distributions were higher than the measured data. All estimates of the most common value were similar to the measured data for the job role of project driller when assessing the percent of the OEL for respirable crystalline silica (Figure 5). For the other three job roles, the blue expert distribution had a wide range when compared to the measured data and other experts.

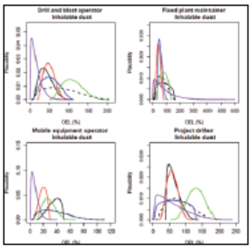


Figure 4. Expert estimates and measured data of inhalable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density), or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black, and green; combined experts are the dashed line. Measured data is presented as purple.

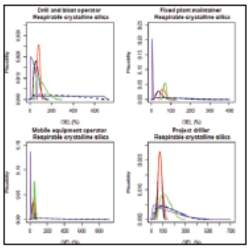


Figure 5. Expert estimates and measured data of respirable crystalline silica percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density), or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black, and green; combined experts are the dashed line. Measured data is presented as purple.

For the assessment of the percent of the respirable dust OEL, the measured data distribution were right skewed except for the job role of mobile equipment operator (Figure 6). The green expert's distributions disagreed with the measured data in all four job roles. All lowest elicited values were in the range of the measured data. For drill and blast operator, all experts had a similar distribution compared with the measured distribution, however the most common value of all the experts was slightly higher compared to the mode of the measured data.

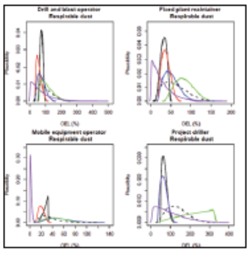


Figure 6. Expert estimates and measured data of respirable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density), or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black, and green; combined experts are the dashed line. Measured data is presented as purple.

4. Discussion

The main purpose of this study was to use expert elicitation to assess the professional judgement of a group of occupational hygienists. We have presented and evaluated a statistical methodology for the encoding of elicited information into distributions from multiple experts. We applied a scaled Beta distribution to expert and measured data; this approach was able to accommodate both left and right skewed distributions as well as "normal" distributions. Our findings suggest that occupational hygienists are inclined to overestimate exposures and that they were more accurate at estimating percentage of OEL than the actual values. Our approach differs from previous research in the way in which exposure assumptions were elicited, by focusing on contaminant concentration and attribution of an exposure standard percentage estimate.

The use of expert knowledge in decision making has been gaining traction in many scientific disciplines, most notably in areas where a traditional approach of utilising observed data may not be a practical option (17-19). The literature relating to human judgment and eliciting expert knowledge with uncertainty proposes that a limited number of simplifying heuristics are used to efficiently arrive at a judgment using available information. These heuristics do not typically utilise all available information and data in a formal algorithmic process but instead use "quick and efficient" rules of thumb to arrive at a judgment. The use of expert knowledge is rapidly becoming a valuable commodity across many disciplines with challenges and opportunities existing around how best to utilise knowledge in problem solving and decision making (26). Occupational hygienists review the workforce, materials, exposure agents, tasks, equipment, exposure controls and identify exposure groups that will be assessed and controlled depending on the final judgments. The exposure evaluation for any job role requires the selection of an OEL and a judgment by the hygienist about where the decision statistic (for example, the 95th percentile of the exposure distribution for the job role) falls in relation to the OEL (14). Professional judgement is considered a 'tool in the toolkit' of the hygienist and serves as a key factor when making a determination on whether an exposure is acceptable in the context of an occupational environment. However, for the most part, subjective qualitative judgments in the field of occupational hygiene have proven to be no more accurate than random chance. This may be because patterns of exposures in many workplaces have a significant degree of uncertainty and unpredictability and there may be little or no data available on these exposure levels. Such situations have been defined as 'low-validity' environments (20) and perhaps somewhat paradoxically, judgement decisions have been shown to be most accurate in these highly uncertain situations, particularly when paired with checklists or models. The use of a checklist that considers consistent inputs is shown to be more reliable at arriving at a judgement than a purely 'human' focussed way but this has not previously been assessed in the occupational hygiene setting (20). (4, 11).

A key observation from this study is the experts' proclivity to consistently overestimate exposures. This appears to be a point of difference when compared to similar studies where there was a significant underestimation bias in the exposure judgments when the range is examined (3, 4, 11). The reasons behind this finding are worth exploring. In other expert elicitation studies (17-19) experts are typically able to estimate the range of measured data distribution quite accurately, however the most common value tends to be higher than the measured value. Our study found that the most common exposure value between the experts and the measured data was higher than the measured value for all contaminants and all job roles for both percentage of the OEL and concentration in all elicitations. We found that the experts lowest exposure value was nearly always (96% of the time) higher than that of the measured equivalent and the highest exposure value was overestimated about half of the time (41% and 54% of the time for percentage of OEL and concentration respectively). These findings suggest that hygienists may be more concerned about the upper bound of an exposure profile as opposed to the lower and therefore concentrated more on estimating this more carefully.

Comparing the expert versus the measured data distributions show that the experts appear to be able to estimate percentage of the OEL more accurately than concentration. This may be attributable to a variety of factors, including risk communication. Given one of the mandates of the occupational hygienist is to 'distil' complex data into easy-to-understand messages for a workforce, many hygienists have taken to expressing results of monitoring data as percentages of the applicable exposure standard and so this way to present data is likely to be more familiar to them.

With respect to the experts, the green expert was notably divergent from the measured data and their elicitations often yielded different results from the other experts. This disparity warrants further investigation into how the green expert executed the elicitations, and whether any cognitive biases attributable to the heuristics of availability, representativeness, and anchoring and adjustment were present during this exercise. A deeper dive into the determinants of the elicited values would provide transparency around the decision-making practices of each expert.

A strength of the study was the statistical encoding of both expert and measured data into scaled Beta distributions. The advantage of the scaled Beta distribution when compared with the normal and lognormal distributions is that it performs better over all levels of skewness, in particular providing accurate encoded values under extreme skewness (28). This is particularly useful when the skewness is expected to be high, or in situations where the degree of uncertainty is high. Both situations are present within the context of this study, and this illustrates why probabilistic methods are attractive to hygienists who are required to make exposure judgments with limited sampling data (37).

A further strength of this study was that we had a large amount of measured data to use for comparison against the expert elicitations. A standard approach to exposure assessment in the field of occupational hygiene dictates randomly sampling 6 - 10 events of a specific job role and calculating an upper tail decision statistic such as the 95th percentile with an upper confidence limit (e.g. 90th or 95th) (14). This approach to exposure assessment has been utilised in the field for many years and was based on the assumption of a stable and predictable work environment wherein a reliable mean and geometric standard deviation can be calculated after 6 – 10 samples (14). With the advent of a more dynamic workforce expected to complete multiple tasks across different work environments (as is the case in the mining industry), the concept of full-shift personal monitoring to define the exposure profile of a job role or similar exposure group (SEG) may not be an optimal approach. Given this, the large dataset in this study was useful in capturing the real distribution of the measured data that may be present in a dynamic work environment (38). With the introduction of sensor measurement technology (sometimes referred to as 'real-time' monitoring) future studies may focus on comparisons between experts and quantitative measurements that are task or source based, which may present a more accurate picture of a worker's exposure in a dynamic occupational environment.

A potential limitation of this study was the number of experts recruited for elicitation. Although there is no absolute guideline on which to base the number of experts invited to provide input, a panel of expert elicitation practitioners determined that at least six experts should be included to ensure robustness of results (39). The same panel also concluded that a point of diminishing returns was reached beyond twelve experts. Future studies may wish to expand the number of experts involved to further broaden the range of experiences that contribute to a person's professional judgement. However, a challenge to these further studies is the availability of both general and industry-specific experts.

5. Conclusions

The results in this study suggest that, in the absence of measured data, occupational hygienists may overestimate exposures. The practical implication of overestimating may be an 'overprotection' of workgroups, or a misallocation of resources such as risk controls, respiratory protection, health surveillance and awareness programs. Conversely, the consequences of underestimating exposure (as has been reported in other studies) may leave workers unprotected. These findings suggest that improved accuracy in exposure assessment is needed. Further efforts should assess the expert's decision-making process and the determinants of their judgements. Future research should focus on these determinants of professional judgement to better assess accuracy and inform formalised training programmes, models, and other tools to improve exposure assessment within the discipline of occupational hygiene.

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38TH ANNUAL CONFERENCE & EXHIBITION

6. Acknowledgements

Funding provided by Rio Tinto. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

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Appendix M: BOHS 2022 Conference proceedings excerpt – published paper 2 (Chapter 5)

Tuesday 21st June

08.30 - 10:00	Registration	Registration & Exhibition – Meet with colleagues and browse the exhibition.		
10:00 - 10:15	Welcome	President, *Chris Keen* BOHS CEO, *Kevin Bampton* Conference Committee Chair, *Dave Flower* **Grand Ballroom**		
10:15 - 11:15	Session 1	Understanding the complexity of respiratory disease transmission – learning from the PROTECT study, Cath Noakes, Professor at University of Leeds		
11:15 - 12:00	Session 2	Impact of COVID-19 on Workplace Stressors. Rachael Jones, Chief Editor - Annals of Work Exposures and Health		
12:00 - 13:15	Lunch and exhibition			
13:30 - 14:45	Parallel Sessions	Session 3a Data *Grand Ballroom*	Session 3b Airborne Contaminants & the Built Environment *Ballroom 4 & 5*	Session 3c Workshop *12th Floor Penthouse*
		shawcity Life saving solutions Product Showcase The Benefits of Live Data & Connected Technology.	CASELLA Product Showcase Vortex3 – An introduction to the latest technology in high flow air sampling	WEL, WEL, WEL... A dive into health-based WELs and how these may impacts on COSHH Regulation 6(1)(a). - Mary Cameron
		Use of expert elicitation in the field of occupational hygiene: comparison of expert and observed data distributions. - David Lowry	Health experiences of the occupants of dilapidated building in the workplace, South Africa. - Mzimasi Mdoda	
		Development of a worker's exposure data collection tool and database system for metals and metalloids. - Steven Verpaele	Development of Quantitative Protection Factors for Personal Protective Devices for Preventing Occupational Diseases Caused by Bioaerosols. - Stephen Larson	
		EXCITE - Flexible data infrastructure to integrate multiple sensor data streams with situational-relevant data to be analyzed, processed, interpreted and visualized. - Maaike le Feber	The Role of Occupational Exposure Limits for Bioaerosols is establishing Health-based Ventilation Standards for the Built Environment. - Stephen Larson	
			The benefits of a cradle to grave approach to Legionella risk mitigation. - Tom Laffey	

Appendix N: ICOH 2022 Conference proceedings excerpt – published paper 2 (Chapter 5)

ICOH 2022

33rd International Congress on Occupational Health

Assessment of professional judgement in the field of occupational hygiene: comparison of expert and observed data distributions

David Lowry (COH)

School of Population Health, Curtin University, Perth, Western Australia

6 - 10 February 2022 | Melbourne – Rome Global Digital Congress, Sharing solutions in occupational health through and beyond the pandemic

STATEMENT SLIDE

I have no conflicts of interest to disclose

2

Overview

- The use of expert knowledge in decision making has been gaining traction in many scientific disciplines, most notably in areas where a traditional approach of utilising observed data may not be a practical option
- The concept of professional judgement in decision making underpins the way in which an occupational hygienist assesses an exposure problem
- Despite the importance placed on professional judgement in the discipline, a method of assessment to characterise accuracy has not been available
- In this study, we assess the professional judgement of a group of occupational hygienists ('experts') when completing exposure assessments on a range of airborne contaminants across a number of job roles within a surface mining environment
- The novel approach of eliciting exposure estimates focusing on contaminant concentration and attribution of an exposure standard estimate was used
- We applied a scaled Beta distribution to expert and measured data; this approach was able to accommodate both left and right skewed distributions as well as "normal" distributions. These elicited fitted distributions were then compared to measured data distributions
- Our findings suggest that occupational hygienists are inclined to overestimate exposures and that they were more accurate at estimating percentage of occupational exposure limit (OEL) than concentration values
- We demonstrate that this elicitation approach and the encoding methodology contained within can be applied to assess accuracy of exposure judgements which will impact on worker protection and occupational health outcomes

Methods

Expert elicitation protocol

- We created a protocol for elicitation which had the experts estimating point estimate values in the following sequence (i) lowest (value the expert would be really surprised if it was less than the measured value), (ii) highest (value the expert would be really surprised if it was more than the measured value), and (iii) most common (estimated most likely value that would lie between estimated 'lowest' and 'highest' values)
- The experts were asked to estimate both concentration and percentage of relevant OEL. An example of elicitation output from one of the experts is given in Figure 1.

		Job role							
Contaminant	Elicitation value	Project driller		Mobile equipment operator		Fixed plant maintainer		Drill and blast operator	
		%OEL	mg/m3	%OEL	mg/m3	%OEL	mg/m3	%OEL	mg/m3
Respirable crystalline silica	Lowest	50	0.05	30	0.03	40	0.04	40	0.04
	Highest	150	0.15	80	0.08	100	0.1	120	0.12
	Most common	80	0.09	50	0.05	60	0.06	80	0.8

Figure 1. Elicitation tool provided to experts showing specific descriptors

Measured data

- The measured data were collected in the form of full-shift, personal samples for the following job roles - project driller, mobile equipment operator, fixed plant maintainer, and drill and blast operator (Table 1)
- The contaminants of interest were respirable crystalline silica, respirable dust, and inhalable dust. Personal samples were collected and analysed as per the applicable Australian Standard for each agent of interest. Workers were selected randomly whenever possible using a random number table
- Point estimate values of (i) lowest, (ii) highest, and (iii) most common (mode) were calculated from the data set in order to define the true nature of the respective exposure profiles.

	Job role			
Contaminant	Project driller	Mobile equipment operator	Fixed plant maintainer	Drill and blast operator
Respirable crystalline silica	n = 220	n = 310	n = 200	n = 210
Respirable dust	n = 220	n = 310	n = 200	n = 210
Inhalable dust	n = 300	n = 350	n = 330	n = 280

Table 1. Personal samples (measured data) collected by contaminant for each job role

Statistical encoding of elicitations

- The majority of the elicited values were strongly left or right skewed, e.g., the most common value was equal to the minimum or maximum elicited value
- Given this, for each expert, a scaled Beta distribution was fitted to each job role and contaminant combination by scaling the elicited values to the range [0, 1]
- A least squares approach was used to estimate the α and β parameters of the Beta distribution by ensuring that the distance between the elicited and encoded quantities was minimised using mean sum of squares (MSS)
- The expert's mode (most common) was defined as $(\alpha - 1)/(\alpha + \beta - 2)$. When the expert's lowest and most common estimate values were the same, then α was set to one and least squares was applied to identify β parameter. Similarly, when the highest and most common estimate values were the same, then β was set to one and α was estimated using least squares
- The function 'optim' in R was employed to search across the parameter space to identify the best α and β parameters that minimise MSS
- To estimate a single distribution which captures the combined experts' values, we applied linear pooling by calculating the sum of the individual expert's distributions
- The measured data were also encoded into scaled Beta distributions. The mode and the lower and upper bounds for the 95% confidence interval were calculated for each job role and contaminant measured data combination
- These summary statistic values were then encoded into scaled Beta distributions using the same methodology as the elicited values.

Results

- Each elicitation took approximately 45-60 minutes to complete, and all experts expressed confidence that the process captured their knowledge of exposure
- Figures 1–3 show the individual and combined expert estimates of exposure concentration (mg/m³) compared with the measured data across the four job roles with respect to each contaminant and Figures 4-6 show values in percentage of the relevant OEL
- Most measured data follow a lognormal distribution, exhibiting right (positive) skewness, and this is observed in 60% of the measured data distributions (all Figures except 2 and 5)

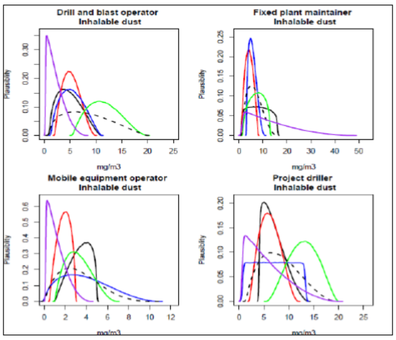

Figure 1. Expert estimates and measured data of inhalable dust concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

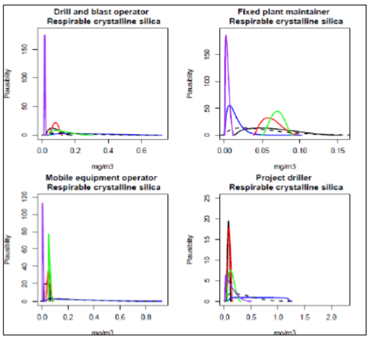

Figure 2. Expert estimates and measured data of respirable crystalline silica concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

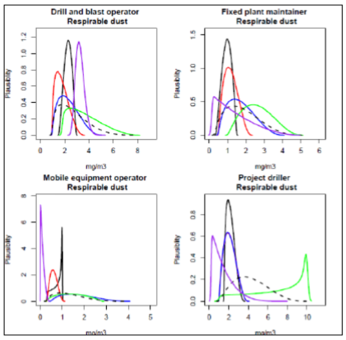

Figure 3. Expert estimates and measured data of respirable dust concentrations. Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

Results

- Comparison of the most common exposure value between the experts and the measured data demonstrate that all experts provided a value higher than the measured value for all contaminants and all job roles, meaning exposure has been overestimated (in some cases, significantly) for both percentage of the OEL and concentration in all elicitations
- For the highest exposure value, the experts overestimated exposure 41% and 54% of the time respectively for OEL and concentration
- For the lowest exposure values experts overestimated exposure 96% of the time for both OEL and concentration when compared with the measured data.

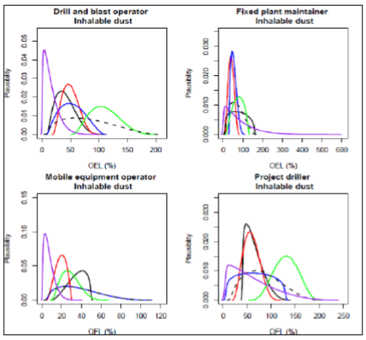

Figure 4. Expert estimates and measured data of inhalable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

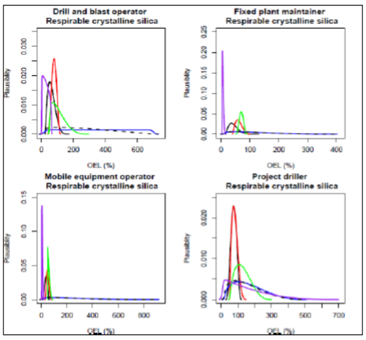

Figure 5. Expert estimates and measured data of respirable crystalline silica percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

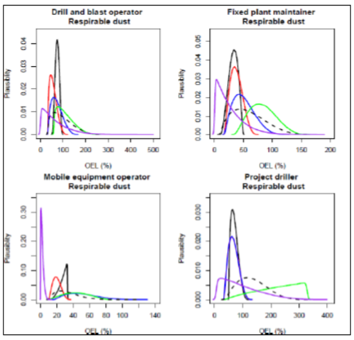

Figure 6. Expert estimates and measured data of respirable dust percentage of occupational exposure limit (OEL). Each curve depicts the experts support (probability density) or measured data encoded into a scaled Beta distribution. Experts are denoted in the colours blue, red, black and green; combined experts are the dashed line. Measured data is presented as purple.

Conclusions

- The main purpose of this study was to use expert elicitation to assess the professional judgement of a group of occupational hygienists
- We have presented and evaluated a statistical methodology for the encoding of elicited information into distributions from multiple experts
- The results in this study suggest that, in the absence of measured data, occupational hygienists may overestimate exposures
- The practical implication of overestimating may be an 'overprotection' of workgroups, or a misallocation of resources such as risk controls, respiratory protection, health surveillance and awareness programs
- Conversely, the consequences of underestimating exposure (as has been reported in other studies) may leave workers unprotected
- These findings suggest that improved accuracy in exposure assessment is needed. Further efforts should assess the expert's decision-making process and the determinants of their judgements
- Future research should focus on these determinants of professional judgement to better assess accuracy and inform formalised training programmes, models, and other tools to improve exposure assessment within the discipline of occupational hygiene.

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I would like to acknowledge the efforts and support of my co-authors, Professor Lin Fritschi, Professor Benjamin J. Mullins, and Dr Rebecca A. O'Leary. Funding provided by Rio Tinto. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

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Appendix O: Descriptive statistics from measured data (Chapter 6)

Drill & Blast Operator

DESCRIPTIVE STATISTICS	Pa2h	dB(A)	%OEL
Maximum (max)	63.848394	103.0	6388.8
Minimum (min)	0.0684148	73.3	6.7
Range	63.779979		
Percent above OEL (%>OEL)	15.152		
Mean	1.299	86.1	128.4
Median	0.881	84.4	87.1
Standard deviation (s)	1.343		
Mean of logtransformed data (LN)	-0.185		
Std. deviation of logtransformed data (LN)	0.892		
Geometric mean (GM)	0.831		
Geometric standard deviation (GSD)	2.440		

Project Driller

DESCRIPTIVE STATISTICS	Pa2h	dB(A)	%OEL
Maximum (max)	28.52003	99.5	2846.8
Minimum (min)	0.0595868	72.7	5.8
Range	28.460443		
Percent above OEL (%>OEL)	86.667		
Mean	5.516	92.4	547.9
Median	1.820	87.6	180.2
Standard deviation (s)	8.211		
Mean of logtransformed data (LN)	0.804		
Std. deviation of logtransformed data (LN)	1.445		
Geometric mean (GM)	2.234		
Geometric standard deviation (GSD)	4.240		

Mobile Equipment Operator

DESCRIPTIVE STATISTICS	Pa2h	dB(A)	%OEL
Maximum (max)	13.33982	96.2	1328.5
Minimum (min)	0.0211422	68.2	2.1
Range	13.318678		
Percent above OEL (%>OEL)	19.149		
Mean	1.621	87.0	160.5
Median	1.162	85.6	114.9
Standard deviation (s)	1.651		
Mean of logtransformed data (LN)	0.023		
Std. deviation of logtransformed data (LN)	0.975		
Geometric mean (GM)	1.023		
Geometric standard deviation (GSD)	2.650		

Fixed Plant Maintainer

DESCRIPTIVE STATISTICS	Pa2h	dB(A)	%OEL
Maximum (max)	37.596722	100.7	3756.0
Minimum (min)	0.0609747	72.8	6.0
Range	37.535747		
Percent above OEL (%>OEL)	32.143		
Mean	3.476	90.4	344.7
Median	1.679	87.2	166.2
Standard deviation (s)	6.334		
Mean of logtransformed data (LN)	0.399		
Std. deviation of logtransformed data (LN)	1.152		
Geometric mean (GM)	1.491		
Geometric standard deviation (GSD)	3.165		

Appendix P: Elicitation instructions and tool (Chapter 6)

Elicitation steps	Elicitation parameter descriptors
1. Review elicitation table on the following tab 2. Work through the elicitation table by placing your best estimation* for each exposure value in the corresponding field 3. Values are required to be given by measurement dose <u>and</u> percentage of the occupational exposure limit (OEL) ***this should be based on your expert opinion and professional judgement***	**Lowest:** Lowest exposure value (value the expert would be really surprised if it was less than) **Highest:** Highest exposure value (value the expert would be really surprised if it was more than) **Most common:** Most common exposure value (estimated most likely value that would lie between estimated 'lowest' and 'highest' values)

Relevent occupational exposure limit (OELs) (for an 8 hour work shift)	Job role descriptors
Occupational noise: 85 dB(A)	**Project driller:** All staff involved in exploration drilling. **Mobile equipment operator:** All occupations that operate heavy equipment including, but not limited to, haul truck drivers, excavators, grader, and loader operators, rubber wheel dozer and track dozer operators. **Fixed plant maintainer:** Process plant maintainers, other than those working in workshops. **Drill and blast operator:** All staff involved in blasting operations.

		Job role							
Contaminant	Elicitation value	Project driller		Mobile equipment operator		Fixed plant maintainer		Drill and blast operator	
		%OEL	dB(A)	%OEL	dB(A)	%OEL	dB(A)	%OEL	dB(A)
Occupational noise	Lowest								
	Highest								
	Most common								

Appendix Q: Feature article from the December 2021 edition of AIOH The Filter Magazine – *'Noise, bias and decision-making – to control, we need to recognise'*

December '21

AIOH AUSTRALIAN INSTITUTE OF OCCUPATIONAL HYGIENISTS 40 YEARS

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FEATURE ARTICLE

Noise, bias and decision making – to control, we need to recognise

David Lowry, MAIOH, COH

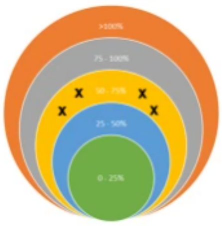
Noise. It is safe to say that in the occupational hygiene world, it is pervasive, persistent, and often very hard to control. However, I'm not talking about the type of noise we measure with a dosimeter or a handheld sound level meter. Consider the following scenario – a group of four hygienists are asked to complete a subjective exposure assessment. The task is relatively simple – each hygienist is asked to estimate the mean exposure to inhalable dust in the same work group by placing their estimation in an exposure category (expressed as a % of the relevant exposure standard). Each hygienist is familiar with the work group and agent in question and feel they are up to the task.

The 'true' exposure category (which has been defined previously through personal sampling) is '50 – 75%', however our hygienists do not know this. The results are shown below in Scenario A, with each estimate denoted by the bold X:

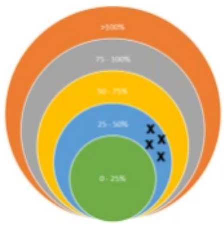
Scenario A

At this point, I'm sure you're all wondering what exactly is going on and what does this have to do with noise. Well, this simple visual display of results is the visual expression of noise, only we are talking about system noise, as opposed to the occupational or environmental variety. The variability that you witness in professional judgment in this infographic is an example of noise, the ubiquitous and often-ignored human failing that is the focus of a well-researched, convincing, and practical book Noise: a flaw in human judgment which was recently written by the psychologist and Nobel Prize winner Daniel Kahneman, former McKinsey partner and management professor Olivier Sibony, and legal scholar and behavioural economist Cass Sunstein. Kahneman won the Nobel Prize in Economic Sciences for his ground-breaking work with Amos Tversky on systematic biases in judgment.

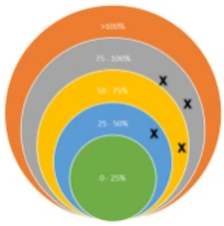
It prompted many psychologists and behavioural economists (including Sibony and Sunstein) to study the causes and remedies for many such faults, including overconfidence, stereotyping and confirmation bias — or seeking, remembering, and placing excessive weight on information that supports our beliefs. In their book Noise: a flaw in human judgment, Kahneman and Co explain a few fundamentals, including that "wherever there is judgement, there is noise" and to also describe the difference between two types of error, noise, and bias. The former being the variability of error, the latter being the average of error. To appreciate the difference visually, let's return to our four hygienists who have now repeated the same exercise, this time with three other workgroups. For simplicity, let's say that the 'true' exposure category is once again '50 – 75%' in the following three scenarios:



Scenario B



Scenario C



Scenario D

Scenario B depicts accuracy in professional judgement in all four hygienists – the estimates of exposure are aligned to the 'true' exposure profile, which we know sits in the 50 – 75% category. Scenario C and D are inaccurate, but in distinctive ways. Scenario C has produced biased results – all estimations do not fit the 'true' exposure category and are clustered together. Scenario D has produced results that can be descried as both noisy and biased – all estimates are inaccurate and there is high variability in the spread of the data.

Many of us are familiar with the term bias. It's one of those concepts that has made its way into our common vernacular, its meaning well-understood as factors that sway judgment in a particular direction. In addition to bias, it turns out there is another, equally significant reason for errors in judgment - noise. Both bias and noise are fundamental concepts which must be understood and accounted for to successfully evaluate science and make the most accurate decisions possible. Noise is the unwanted variety in a set of responses, or judgments about something - unwanted because the variability is not beneficial but rather represents deviation, or error. As we have seen in the above examples, a noisy system is one that has a large variation in decisions pertaining to a given topic. Importantly, bias and noise exist independently of one another but are both always present to some degree in human decision making. Ultimately, the aim is to improve accuracy by reducing the unwanted variability (noise) and average error (bias) in the decision making process, but how do we do this?

In their book, Kahneman and Co outline a process for identifying and preventing noise to improve decision making accuracy. The first step is to undergo a 'noise audit' to assess the degree of noise in a given system. This audit involves evaluating a set of judgments and asking the question - "how much variation is there between independent judgments?" The second step in the process addresses ways to prevent noise by employing procedures called 'decision hygiene' practices. The goal is to produce an independent, fact-based evaluative judgement. Some suggestions to reduce noise include aggregating and averaging the independent assessments and imposing structure for assessments. The authors also mention that absolute scales have more noise than relative scales. As a more extreme solution to reduce noise, human decision making can sometimes be removed altogether and replaced with algorithms. Clearly, using rules and algorithms to replace human judgment has the potential to introduce its own systematic bias (not to mention that an actual person must program the machines).

This is all very relevant to us as Occupational Hygienists. A cornerstone of our profession is our decision making and professional judgement, sometimes deployed in the absence of quantitative data and in the presence of high uncertainty. Accurate decision making builds trust and credibility, whereas inaccurate decision making can leave workers unprotected or at risk of harm. To make effective judgements, we not only have to have information, but we also need a system and process in place for navigating bias and noise, respectively. As a starting point, one of the first steps we can take is to have a general awareness of the pervasive nature of both types of error in judgement.

References

Kahneman, D., Sibony, O., & Sunstein, C.R. (2021). Noise: a flaw in human judgement. First edition. New York: Little, Brown Spark.

Appendix R: Social media engagement for published articles