Improved Methods for Evaluating Noise Exposure and Hearing Loss

By

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List of Abbreviations, Acronyms, and Symbols

ACGIH	American Conference of Governmental Industrial Hygienists
AIC	Akaike Information Criterion
AL	Action Level
ANOVA	Analysis of Variance
ANSI	American National Standard Institute
BLS	Bureau of Labor Statistics
CHABA	Committee on Hearing Bioacoustics, and Biomechanics
CHD	Coronary Heart Disease
CSV	Comma Separated Values
CVD	Cardiovascular Disease
DALY	Disability-Adjusted Life Years
dB	Decibel
dBA	A-Weighted Decibel
DOL	Department of Labor
ER	Exchange Rate
HCP	Hearing Conservation Programs
HEG	Homogenously Exposed Groups
HSD	Honest Significant Difference
HTL	Hearing Threshold Levels
Hz	Hertz
i.i.d	Independent and Identically Distributed
IEC	International Electrotechnical Commission
IQR	Interquartile Range
ISO	International Organization of Standards
JEM	Job-Exposure Matrix
kHz	Kilohertz
LAVG	Average Sound Level
LEQ	Equivalent Continuous Noise Level
MSHA	Mine Safety and Health Administration
NHANES	National Health and Nutrition Examination Survey
NIHL	Noise-Induced Hearing Loss
NIOSH	National Institute for Occupational Safety and Health
NIPTS	Noise-Induced Permeant Threshold Shift
NTLAN	Hearing Loss Associated with Age and Noise
O*NET	Occupational Information Network
OSHA	Occupational Health and Safety Administration

Pa	Pascal
PEL	Permissible Exposure Limit
REL	Recommended Exposure Limit
REML	Restricted Maximum Likelihood
SLM	Sound Level Meter
SOC	Standard Occupational Classification
TLV	Threshold Limit Value
TWA	Time Weighted Average
μPa	Micropascal
VA	Veterans Administration

Abstract

Noise is one of the most common occupational exposures in the United States; up to 22 million workers are exposed to dangerous noise levels each year. Excessive noise exposure can lead to noise-induced hearing loss (NIHL). Exposure to high levels of noise may also be a contributing factor for a number of non-auditory outcomes, including injuries, cardiovascular disease, stress, and depression. This dissertation research focused on improving our understanding of the relationship between occupational noise exposure and NIHL by completing three distinct but related projects.

Project 1 investigated the feasibility of using smart devices (iPods and iPhones) to accurately measure occupational noise in laboratory experiments and real-life workplaces. This project was divided into four experiments, three of which took place in a controlled laboratory setting, and one of which was a field test of the devices in two groups of workers. Experiment 1 demonstrated that certain combinations of applications and microphones could provide measurements within +/ 2.0 A-weighted decibels (dBA) of a reference noise level. Experiment 2 showed that the best-performing microphone and application combinations could provide measurements within +/- 2.0 dBA of a reference level across different generations of devices. Experiment 3 demonstrated that the 8-hr time weighted average (TWA) measured by the smart devices was within +/- 1.5 dBA of a paired noise dosimeter. Finally, experiment 4 determined that, on average, smart devices overestimated workplace exposures by up to 2.2 dBA among workers exposed to highly variable noise.

Project 2 developed a job-exposure matrix (JEM) for every occupation in the United States. This was done by collecting data from the government, private, industry and the published literature. From this dataset 748,598 measurements made using the Occupational Health and Safety Administration's (OSHA) Permissible Exposure Limit (PEL) were used to impute exposures for occupations without measurement data. Each measurement was assigned a job title based on the Bureau of Labor Statistics' (BLS) standard occupational classification (SOC) system. Because this classification system is hierarchical, it was possible to impute values for SOCs using SOCs where data was available. Of 443 SOCs, 19% and 74% were estimated to have noise exposures >85 dBA and >80 dBA, respectively, although many SOCs had wide credible intervals, indicating a significant amount of uncertainty around the point estimates.

Project 3 compared the ability of the OSHA PEL and the National Institute of Occupational Safety and Health's (NIOSH) Recommended Exposure Limit (REL) to predict NIHL. Noise exposures were estimated for a previously established cohort of construction workers followed for 10 years using both the PEL and REL metrics. These exposure estimates were used in mixed models predicting hearing threshold levels (HTLs). Akaike information criterion (AIC) was calculated to evaluate model fit. The modeled estimates were also compared to hearing loss estimates from an International Organization of Standards (ISO) NIHL model. In all but one instance, the models using the REL were found to have a better model fit. The mixed models predicted more hearing loss than the corresponding ISO model; however, the REL showed closer agreement to the corresponding ISO model than the PEL.

The completion of these projects have made it easier to collect and use occupational noise measurements for epidemiological purposes. In addition, this research will help inform best practices for collecting occupational noise measurements to that they can be used to better predict NIHL.

Chapter 1 - Introduction

Introduction

Noise is a generic term used to describe unwanted sound. Depending on the frequency, intensity, and source of noise, exposures can be merely an annoyance or a major detriment to human health resulting in not only hearing loss but also increased risk of cardiovascular disease and injury.[1–4] Noise in community environments can result from many different sources, including road traffic, aircraft, construction sites, and heavy industry.[5] Exposure to noise in the workplace typically occurs at much higher sound pressure levels than in communities. An analysis of self-reported data from the National Health and Nutrition Examination Survey (NHANES) estimated that as many as 22 million workers are exposed to hazardous noise each year.[6] The number of cases of noise induced hearing loss (NIHL) is difficult to track. The Occupational Health and Safety Administration (OSHA) only began to require employers to record NIHL as a specific category of occupational disease in 2002; prior to this date hearing loss was only recorded if it resulted in an employee missing a day of work, which rarely occurs.[7] An analysis conducted by Masterson et al. found that prevalence of hearing loss from 2006 to 2010 ranged from about 12 to 25% for noise exposed workers depending on their industry of employment.[8] A later study looking at the annual number of disability-adjusted life years (DALYs) attributed to hearing loss found that across all industries an estimated 2.53 healthy years were lost each year per 1,000 noise-exposed workers in the US.[9] While the exact prevalence of NIHL is unknown it is reasonable to surmise that NIHL affects hundreds of thousands of workers in the US.

NIHL consistently ranking as one of the most common workplace injuries and has a significant economic impact, with an estimated cost of $242 million in worker's compensation alone in the United States every year.[6] This is in addition to the estimated $1 billion spent by the Veterans Administration (VA) every year in compensation for NIHL and tinnitus.[10] The exact financial cost of hearing loss, outside of direct compensation, is difficult to estimate, as there are very few published studies, and those that do exist use different assumptions in calculating the financial burden of hearing loss. A study in 2000 estimated that, depending on the age of onset, profound hearing loss (>70 dBA) could cost between $900 and $965,000 per adult. This study included lost productivity, special services, and direct medical costs in their calculations.[11] The World Health Organization estimates that the total cost of hearing loss in the US may range between $30 and $300 billion.[12] A more recent study estimated that if the 20% of US hearing loss represented by NIHL was prevented it would save between $58 and $152 billion annually.[13]

Measurement of Occupational Noise Exposures

OSHA currently sets a permissible exposure limit (PEL) for occupational noise exposure at 90 A-weighted decibels (dBA) with a 5 dB exchange rate (ER), and 90 dB threshold as an 8 hr-TWA. Measurements made using the OSHA criterion are denoted as average levels, L_{AVG}.[14] The ER is a value used to determine the allowable exposure time at a given level of noise exposure. As an average exposure is increased by the ER the allowable exposure time is halved; conversely if a noise exposure is decreased by the ER, the allowable exposure time is doubled. [15] The National Institute for Occupational Safety and Health (NIOSH) sets its Recommended Exposure Limit (REL) for noise at 85 dBA with a 3 dB ER, and with an 80 dB threshold as an 8hr-TWA. Measurements made using the NIOSH criterion are referred to as equivalent continuous average levels and denoted by the term L_{EQ}. [16] The recommended standard put forth by NIOSH does not account for technical and economic feasibility and as a result is not legally enforceable, while the regulation promulgated by OSHA is enforceable as well as having been determined to be economically and technically feasible. The criterion adopted by NIOSH is more protective as it has a lower exposure limit and a more conservative ER.

Figure 1-1 illustrates the difference in allowable exposure time using the OSHA and NIOSH criteria. There is a substantial difference in allowable exposure time between the two criteria. While the difference between 85 and 90 dBA criterion levels may not appear large, it is important to consider that, given the log scale on which decibels are computed, an increase in 3 dBA results in a doubling in sound energy. At this time most other industrialized nations, including China and countries in the European Union, have adopted an 85 dBA exposure limit with a 3 decibel ER, essentially mirroring the NIOSH REL.[15]

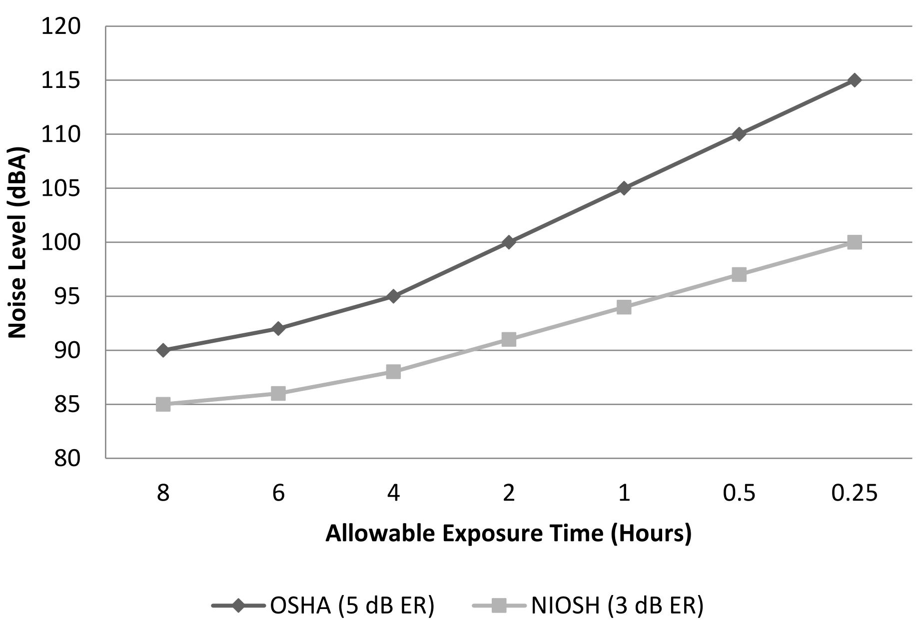

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Figure 1-1 Allowable exposure time using the OSHA and NIOSH noise criteria

Two different types of devices are typically used to measure broadband (i.e., not frequency-specific) occupational noise exposure. The first is a sound level meter (SLM). These devices can vary from very simple units that only provide an instantaneous measure of noise levels to sophisticated devices capable of data logging measured levels over intervals of time and providing simple statistical measures. There are two classifications for field-applicable SLMs: Types 1 and 2. Type 1 SLMs are considered precision, laboratory-grade instruments and are accurate within 1 dBA of a reference noise, type 2 SLMs are used for general purpose measurements and are accurate within 2 dBA of a reference noise.[17] Type 2 SLMs are most commonly used by occupational health practitioners.

While these devices can be placed in a worker's hearing zone (a 30 cm sphere around the worker's head) for measurements of short duration, they are cumbersome and better suited for area noise surveys.[14] To measure an individual worker's daily exposure, noise dosimeters are used. As with SLMs, dosimeters are classified as Type 1 or Type 2 and can range from simple devices that only record the average noise level (L_{EQ} or L_{AVG}) over their run time to devices that can log average, minimum, maximum, and other noise metrics over time using multiple criteria simultaneously.[17]

The microphones in both SLMs and dosimeters measure sound pressure in pascals (Pa) because the human ear can detect sounds from 0.00002 (20μPa) to 20 Pa the decibel (dB) notation is commonly used. The decibel is a dimensionless measurement that is based on the logarithm of a ratio of the sound pressure level and a reference sound pressure level, which is usually 20μPa.[18] Measurements are made across a wide frequency range typically 20-20,000 hertz (Hz). Fletcher and Munson recognized that humans perceive some frequencies of noise better than others, based on this research several weighting factors were developed to adjust for susceptibility of hearing loss at different frequencies.[19] This has resulted in all modern noise measurement devices that measuring noise using A-weighted decibels (dBA). These devices can measure noise using either a slow (1-second) or fast (0.125-second) measurement interval depending on the type of noise being measured.[17] Typical sound level meters can measure noise levels up to 120 dBA. Modern devices can integrate the measured noise exposure and provide an estimated 8-hr time weighted average (TWA) based on the threshold setting (i.e. the level of noise that must be reached before it is added to the overall dose), exchange rate (e.g. the doubling or halving time), and the criterion level.

Type 1 and 2 dosimeters and SLMs typically cost hundreds to thousands of dollars. Because of the cost of purchasing SLMs and dosimeters there is a growing interest in utilizing ubiquitous personal handheld smart devices (e.g., smart phones, tablets, etc.) to measure noise exposure. In 2014, Kardous and Shaw were the first to evaluate the feasibility of using these devices to measure noise in a laboratory setting and found that smart devices could be used to reliably measure noise exposure in some instances.[20] A study released later that year by Nast et al. found the opposite to be true. [21] Because the number of smart devices continues to grow each year, one of the aims of this dissertation was to expand on the work conducted by Kardous and Shaw and further evaluate the feasibility of smart devices to supplement or replace noise dosimeters as the device used to measure occupational noise exposure.[22]

Effects of Noise Exposure on Human Hearing

The human ear is divided into three parts: the outer ear, middle ear, and inner ear. The outer ear consists of the pinna, external auditory meatus (ear canal), and tympanic membrane (eardrum). The pinna serves to focus the sound wave in to the ear cannel. The shape of the pinna amplifies sounds in the 2-4 kHz range by as much as 15 dB[23]. Once in the ear cannel, the sound wave vibrates the tympanic membrane (eardrum) which transmits the sound to ossicular bone chain.[24] The middle ear consists of three ossicular bones (the malleus, incus, and stapes) which transfer the sound wave from the air-filled cavities of the outer and middle ear to the cochlea, which demarcates the inner ear.[25] The ossicles further mechanically amplify the frequency range of 2-4 kHz, which is why human hearing is more sensitive – and more vulnerable to noise exposure – in those frequencies [23].

The cochlea is a fluid filled spiral-shaped tube in the inner ear which converts the physical energy of sound waves to electrical energy interpreted by the brain as sound. When a sound wave enters the cochlea it causes a compression of the fluid in the inner ear which creates a wave that passes over the basilar membrane.[25] Depending on the frequency of the sound wave the fluid will compress different locations along the basilar membrane, which contains hair cells that are critical for hearing. Higher frequency sounds will compress fluid at the base of the membrane, while lower frequency sounds will compress fluid at the apex of the membrane. The compression of the membrane will bend stereocilia, which are organelles of the hair cells that generate nerve impulses which are then sent along the auditory nerve to the brain.[25,26]

The most well-known health effect of hazardous noise is its effects on human hearing. NIHL is characterized by reduced hearing sensitivity at particular frequencies (3,000, 4,000, or 6,000 Hz), with a recovery at 8,000 Hz[27] and frequencies of 2000 Hz and below. It has been found that occupational exposure to 80 dBA of steady state noise over ten years produces very little hearing loss while 85 dBA for ten years will result in about 10 dB of hearing loss at the most sensitive frequencies.[15] As noise levels increase, a greater amount of hearing loss occurs across all audiometric frequencies as seen in figure 1-2.

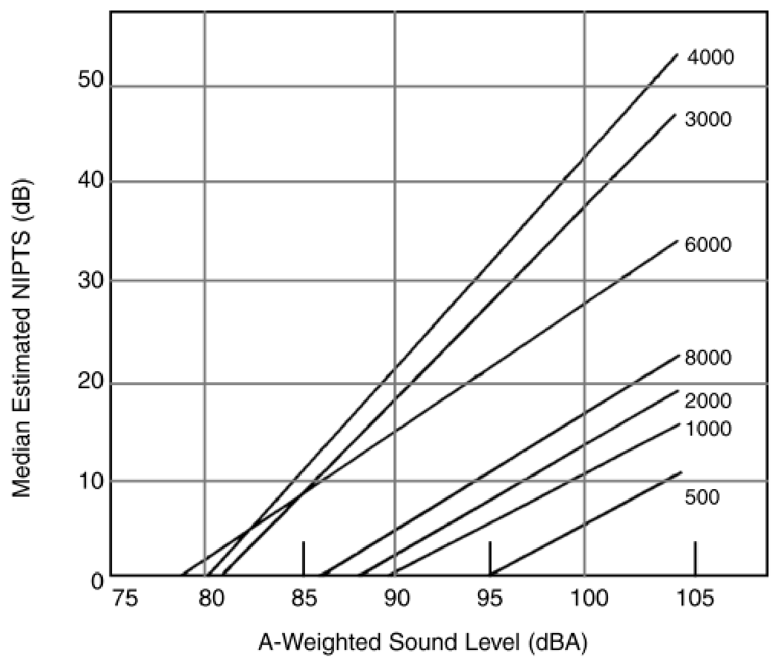


Figure 1-2 Estimated occupational noise induced permanent threshold shifts at various frequencies produced by 10 years or more of exposure to noise (Reprinted from the Noise Manual 5th Edition)

Hearing loss can result from two different types of damage, conductive and sensorineural. Conductive hearing loss occurs when the outer or middle ear are damaged in such a way that it interferes with the sound wave entering the ear and being transferred to the cochlea. This is less common in adults than sensorineural hearing loss and is primarily caused by infection, physical trauma from accidents or impulse noise.[14] This type of hearing loss can often be treated by antibiotics or surgical procedures depending on the etiology of the condition causing hearing loss.[28,29] Conversely, sensorineural hearing loss is caused by damage in the inner ear. This is most commonly caused by hazardous noise exposure; which can either be chronic continuous noise, or few (or even one) impulsive noise transients, and can also occur naturally as a person ages (presbycusis) and is exposed to noise outside of the workplace (sociocusis).[30,31] Hazardous noise causes the stereocilia in the cochlea to shear off at the base and become fused into giant cilia or disappear entirely. This reduces the electrical signals sent to the brain when a sound wave enters the inner ear resulting in irreversible hearing loss.

Audiometric evaluations are used to determine the change in hearing over time, which may be the result of noise exposure during the interval between tests. According to both the OSHA noise standard, and recommended practice, workers should receive a baseline audiogram before employment or being assigned to an area with hazardous noise. The test measures pure-tone hearing threshold levels (HTLs) at various audiometric test frequencies (0.5, 1, 2, 3, 4, 6, and sometimes 8 kHz) after a quiet period of at least 14 hours. The worker is then given a follow-up audiogram annually. Each audiogram is compared to the baseline to determine if hearing loss has occurred. Figure1-3 shows an example of an audiogram demonstrating normal hearing (blue line) and a notch at 4,000 Hz (red line), as well as various gradations of hearing loss.

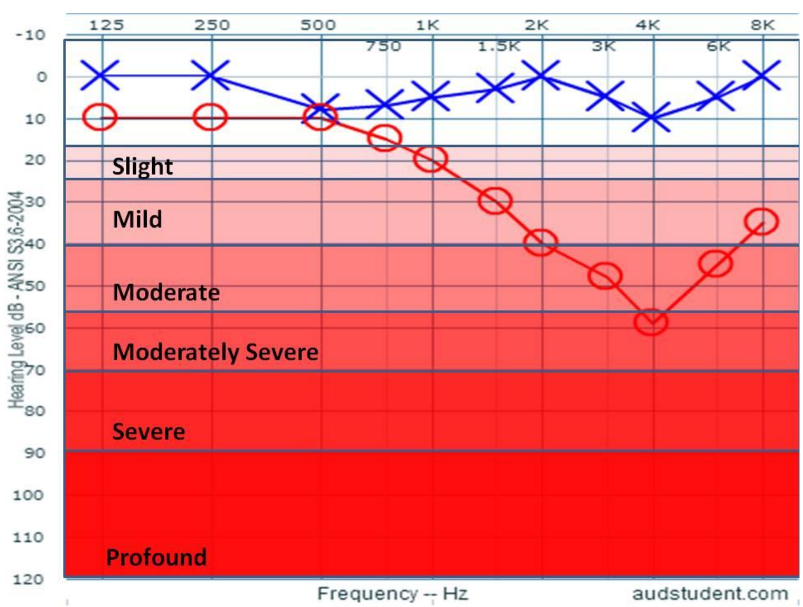


Figure 1-3 An example of an audiogram for normal (blue) and abnormal hearing (red)

Unlike other occupational exposures that may have noticeable acute health effects, NIHL develops over a long period of time in most cases. A temporary, reversible shift in audiometric thresholds may occur before permanent NIHL occurs. However it is not known whether a temporary threshold shift may increase the risk of hearing loss later in life.[26,32] On an individual level NIHL can greatly reduce a person's quality of life by limiting their economic potential and isolating them from their family members and friends. [33,34] NIHL also creates a large economic burden for healthcare systems that treat those who have suffered hearing loss from hazardous noise exposure. Both the personal and societal burdens are preventable by properly controlling hazardous noise exposures.

Non-Auditory Effects of Occupational Noise Exposure

Studies in a variety of industries over the past two decades have indicated that workers who are exposed to high levels of noise (>85 dBA, either as a TWA or as a brief exposure) experience injuries at higher rates than those exposed to low levels of noise.[35–38] Workers who had their hearing impaired either by hearing loss or hearing protection were also found to have higher rates of injuries. This may be due to the difficulty in communication or perceiving warning sounds in the workplace.[39–44] Some studies suggest a combination of occupational noise exposure and NIHL can increase the risk of occupational accidents. [45,46]

Occupational noise exposure may also be associated with adverse cardiovascular health outcomes. From a public health standpoint, hypertension affects about 67 million people in the US; while coronary heart disease (CHD) is currently the leading cause of death among men and women in the US, costing the US healthcare system billions of dollars each year.[47] There is also evidence that noise exposure can result in increased hypertension many hours after the exposure has ceased.[48,49] Several cross-sectional and cohort studies have found an association between chronic occupational noise exposure and hypertension.[50–54] While increased blood pressure is a risk factor for CHD, studies have found an association between occupational noise exposure and

CHD when adjusted for increased blood pressure.[4,49,55,56] Melamed et al. 1997 found that men less than 44 years old that were exposed to greater than 80 dBA during their work shift had higher levels of total cholesterol and triglycerides then men exposed to lower levels of noise. Additionally, men who were exposed to greater than 80 dBA and reported a high level of noise annoyance had a significantly higher mean cholesterol level (p=0.003) than those who were exposed to below 80 dBA and reported a low level of annoyance. [55] Virkkunen et al. 2005 further speculated that the mechanism for noise-induced CHD goes through "the noise-stress-metabolic syndrome pathway".[4] However, the authors acknowledged the difficulty in determining whether hypertension has a mediating or confounding effect on CHD [4] There is still insufficient evidence as to whether there is a mechanism where noise exposure increases the risk of CHD independent of hypertension status.

Finally, occupational noise exposure can also lead to increased psychological stress, both in and outside the workplace. [57,58] If left unaddressed, workplace stress can lead to depression, chronic fatigue, concentration, and sleep problems; all of which can decrease workplace efficiency and lead to more workplace accidents.[57–60] Community noise can also make it difficult to fall asleep or stay asleep.[61,62] Sleep disturbance is also a risk factor for cardiovascular disease (CVD) which further complicates the relationship between noise exposure and CVD.

Motivation for Research

Despite the ubiquitous nature of noise exposures, there are still many gaps in our knowledge of occupational noise exposure. The vast majority of noise measurements take place in mining, manufacturing and other industrial settings.[63] This is due to the fact that these occupational environments have obvious sources of hazardous noise. These industries often have the resources to establish and maintain hearing conservation programs which provide guidelines to monitor exposures and maintain records of employee's hearing levels. For example, OSHA requires that employers identify workers who are exposed to more than 85 dBA as an 8-hour TWA and provide hearing protection devices and yearly audiometric tests to monitor a worker's hearing.[64] However, many jobs in service, construction, and other industries have the potential for hazardous noise exposure and have not been adequately evaluated. Even in industries where noise monitoring has traditionally been conducted there are still gaps in our understanding of noise exposure profiles. This is due in part to the costs and time required to implement a robust noise monitoring program.

The second and third chapters of this dissertation pertains to research conducted to help lower the economic and technical barriers to collecting high quality noise exposure data. This was done by evaluating the feasibility of using commercially available personal handheld smart devices (e.g., smart phones.) and commercially available applications ("apps") for these devices designed to measure noise exposure. Measurements made with smart devices, apps, and internal and external smart device microphones in laboratory and workplace settings were compared to traditional noise measurement instruments to assess the accuracy of measurements made with the smart devices.

The fourth chapter of this dissertation describes the development of a large dataset of occupational noise measurements and use these measurements to construct a job-exposure matrix (JEM) for all occupations in the US and Canada. This was accomplished by collecting noise exposure data from the published literature, government agencies, consulting groups, and private industries. The collected data were cleaned and standardized to the Bureau of Labor Statistics (BLS) Standard Occupational Classification System (SOC). Taking advantage of the hierarchal structure of the SOC system, it was possible to use imputation to estimate noise exposure for occupations that did not have any data allowing for the construction of a completed JEM that can be used by researchers and practitioners to estimate occupational noise exposures by job title.

The fifth chapter of this dissertation describes the reanalysis of a dataset from a cohort of construction workers followed for 10 years and described by Seixas et al. in 2012.[65] Seixas et al used the NIOSH exposure assessment criteria (e.g., 85 dBA exposure limit and 3 dB ER) to calculate noise exposure for the workers in the study. Hearing threshold levels were tracked throughout the study and linear mixed models were used to predict hearing threshold levels based on noise exposure and other factors. There is some debate on whether the NIOSH criteria or OSHA criteria (e.g., 90 dBA exposure limit and 5 dB ER) is more predictive of NIHL risk. This debate is centered primarily on the difference in ER between the two criteria. Data and measurements available on the cohort provided an opportunity to recalculate the cohort's noise exposure using the OSHA criteria, and to then compare the predictive power of the two noise metrics by comparing the corresponding model fit and comparing model predictions to the International Organization of Standards' (ISO) standard models of NIHL.

The completion of the projects described in chapters two, three, and four have made it easier, less resource-intensive, and more financially feasible to conduct exposure assessments for noise. It has also made it possible, for the first time, to synthesize noise measurements from multiple sources and use that information to better prioritize further noise sampling and predict hearing loss based on a person's occupation. The completion of the project in chapter 5 contributes to the ongoing scientific debate regarding whether the 5 and 3 dB ER is more appropriate. The project has important implications for the first two projects, as it will provide guidance for how measurements should be made using smart devices and it will also give insight into which measurement criterion in the JEM provides a better measure of exposure.

Chapter 2 -Improving the Accuracy of Smart Devices to Measure Noise Exposure

Abstract

Occupational noise exposure is one of the most frequent hazards present in the workplace; up to 22 million workers have potentially hazardous noise exposures in the US. As a result, noise-induced hearing loss is one of the most common occupational injuries in the United States. Workers in manufacturing, construction, and the military are at the highest risk for hearing loss. Despite the large number of people exposed to high levels of noise at work, many occupations have not been adequately evaluated for noise exposure. The objective of this experiment was to investigate whether or not iOS smartphones and other smart devices (Apple iPhones and iPods) could be used as reliable instruments to measure noise exposures. For this experiment three different types of microphones were tested with a single model of iPod and three generations of iPhones: the internal microphones on the device, a low-end lapel microphone, and a high-end lapel microphone marketed as being compliant with the International Electrotechnical Commission's (IEC) standard for a Class 2-microphone. All possible combinations of microphones and noise measurement applications were tested in a controlled environment using several different levels of pink noise ranging from 60 to 100 dBA. Results were compared to simultaneous measurements made using a Type 1 sound level measurement system. Analysis of variance and Tukey's honest significant difference (HSD) test were used to determine if the results differed by microphone or noise measurement application.

Levels measured with external microphones combined with certain noise measurement applications did not differ significantly from levels measured with the Type 1 sound measurement system. Results showed that it may be possible to use iOS smartphones and smart devices, with specific combinations of measurement applications and calibrated external microphones, to collect reliable, occupational noise exposure data under certain conditions and within the limitations of the device. Further research is needed to determine how these devices compare to traditional noise dosimeter under real-world conditions.

Introduction

Smartphones have become ubiquitous in the United States; in 2011 the US Census Bureau estimated that 73.5% of people over the age of 25 used smartphones.[66] In addition to providing a convenient form of communication, these devices have the ability to run computer programs referred to as applications or “apps”. Using the processing power of these devices many companies have applications that can be used to track a user’s behaviors, fitness and health.

A large number of applications that may be useful to environmental health professionals and industrial hygienists are available from various sources. Many of these apps provide a convenient way to record safety and health audits, look up regulations or exposure limits, or evaluate centrally-monitored exposure conditions (e.g., heat, weather conditions, or air pollution levels) on a mobile device. Other applications are used as companions to external sensors that communicate wirelessly with the smartphone. One of the most common occupational exposures that smartphone applications are able to measure is noise, as every smartphone is built around a microphone designed to record voices for communication.

Noise is one of the most common occupational exposures. It is estimated that over 22 million people each year are exposed to levels of noise in excess of 85 A-weighted decibels (dBA) as a time weighted average (TWA).[16] Most professional sound level meters (SLMs) and noise dosimeters are costly to purchase or rent and often require proprietary software to analyze the collected measurements. While it is unlikely that smartphones or smart devices will replace traditional noise measurement devices for compliance purposes, they have the potential to be used as low cost survey tools. Additionally, these devices have immense value in providing "crowd sourced" data for environmental noise levels; in fact, several projects are currently underway that have attempted to map the noise of certain areas.[67,68] Finally, there is a potential for these applications to be useful in developing countries or low income areas where cheaper versions of smartphones are available, but it is not feasible to use a professional sound level meter or noise dosimeter.[22]

The potential opportunities presented by noise measurement applications are obvious given the prevalence of smartphones, their ease of use, and low cost compared to traditional noise measurement devices. Despite the best efforts of the developers, these applications have not been harmonized to any performance standard. The most comprehensive review of smartphone applications that measure occupational noise was conducted by Kardous and Shaw of the National Institute for Occupational Safety and Health (NIOSH) in 2014,[20] and found that a small number of applications (4 out of 192 applications tested) offer the functionality and accuracy to be potentially useful for making occupational noise measurements. A subsequent study by another group found that even the best application evaluated was not accurate enough to make reliable noise measurements.[69]

In light of these conflicting results it is clear that further research into the accuracy of noise measurement applications is needed. As Kardous and Shaw indentified, different models of the same smartphone platform (iPhone, Apple Inc, Cupertino, CA) performed differently. This is an issue, especially for Android-based devices, as hundreds of models of smartphones with differing components and operating systems are manufactured each year by multiple manufacturers, and each of these factors could potentially lead to large variations in measurements. In addition, it is not always easy or possible to calibrate the internal microphone of a smartphone, which can lead to systematic error in measured levels. Some applications have a feature to automatically calibrate to a certain microphone, but the effectiveness of this feature has not been independently evaluated. Finally, the size and fragility of the smartphone makes it impractical to be used as a personal noise exposure instrument by mounting it in an individual's hearing zone – a hemisphere around the person's ear with a radius of approximately 18 inches.[18] If a smartphone's microphone is physically covered by clothing or other materials it is likely that the smartphone would not make an accurate measurement.

To further assess approaches to smartphone-based noise exposure assessment, we compared the accuracy of smartphone noise measurements across different smart devices and applications. We also evaluated the accuracy of measurements made using the devices' internal microphone, as well as using two external microphones, an approach which has been discussed, but not been utilized previously.

Methods

The three applications found by Kardous and Shaw (2014) to perform the most accurate A-weighted noise level measurements were selected for further consideration since they met the NIOSH criteria for functionality and accuracy in this experiment. These applications were

NoiSee (EA LAB), SPLnFFT Noise Meter (Fabien Lefebvre), and SoundMeter (Faber Acoustical, LLC) all of which are available on the iTunes Store.[20] Only applications available on the iOS operating system were considered. This was done because the iOS operating system is more tightly controlled than other mobile operating systems and Apple devices have more uniform hardware than Android devices. This design choice will limit the generalizability of the results to only iOS devices. The chosen applications ranged in price and features (Table 2-1). All of the applications allowed for a user to select different measurement standards for integrating noise exposure. SPLnFFT and SoundMeter both allowed for user-customized threshold, criterion level, and exchange rate, which allows for greater flexibility in making measurements. Only SPLnFFT and SoundMeter allowed for the export of stored measurements as a comma separated value (.csv) file that can be opened in a spreadsheet program.

Application	**Developer**	**Weightings**	**Standards**	**Exchange Rate**	**Projected Dose**	**Data Export**	**Price**
NoiSee	EA Lab	A, C, Flat	OSHA/ISO	3, 4, 5	Yes	No	$0.99
SPLnFFT	Fabien Lefebvre	A, B, C, Flat	Custom	3, 4, 5	Yes	Yes [A]	$3.99
SoundMeter	Faber Acoustical	A, C, Flat	Custom [A]	3, 4, 5 [A]	Yes [A]	Yes [A]	$20.00

[A] Requires additional in-application purchases for an additional $20

Table 2-1 Summary of chosen applications and features

Three different Apple device models were evaluated during this experiment, all of which used the latest version of iOS (8.1, except for the iPhone 4 which used iOS 7.1). Three 5th generation Apple iPods were the primary devices used. iPods are very similar to iPhones except that they lack the ability to communicate with cellular networks. These devices were chosen because they are cheaper to acquire than iPhones, which makes them more practical to deploy. In addition to these devices, the iPhone 4, 4S, and 5S were all evaluated to compare their ability to measure noise levels and provide some insight into the effects of the slight hardware differences between the models. The applications that were evaluated were identical across the different devices.

In addition to evaluating the internal microphones on the devices two additional external microphones were used. One microphone was the iMM-6 Calibrated Measurement Microphone from Dayton Audio (Springboro, OH) and the other was the i436 microphone from MicW (Beijing, China), which complies with the IEC's)standard for a Class2 SLM which has a tolerance of +/- 1.4 dB at 1000 Hz.[70–72] Both microphones have a 3.5 mm audio plug that connects to the headphone jack on smart devices. The microphones were calibrated to 94 dB SPL using the application's calibration setting and a Larson Davis (Provo, UT) Cal 150B SLM calibrator before the start of the experiment.

The first experiment evaluated the influence of internal vs. external microphones on variability in measured noise levels in the same type of devices running the same applications. This was done by placing three 5th generation Apple iPods in a reverberant noise chamber at the NIOSH acoustic testing laboratory in Cincinnati, OH. A diffuse sound field could was generated to prevent the location of the device's microphone from influencing the results. Pink noise was generated through three JBL XRX715 two-way loud speakers using the REATPLus software (ViAcoustics, Austin, TX). Sound level measurements were obtained through the Trident Multi-Chanel Acoustic Analyzer Software (ViAcoustics, Austin, TX) using a Larson Davis 2559 ½" inch microphone. The entire system simulates a Type 1 sound level measurement instrument.

Pink noise was generated at 60 dBA and the chamber was allowed 20 seconds to ensure that a stable sound field was established so that the devices would provide a stable reading. Using a USB webcam, measurements from the screens of the 3 devices were recorded and observed remotely, eliminating the need to re-enter the reverberant chamber to record measurements. After the measurements were recorded, the sound level was increased by 5 dBA and allowed to stabilize. This process was repeated in 5 dBA increments up to 100 dBA. This was done 6 times for each combination of microphone and application, so that each of the 3 devices made 54 measurements for each combination of application and microphone, or a total of 162 measurements for each combination of the application and microphone. In total, 1,458 measurements were made in experiment 1.

The results were recorded in Excel (Microsoft, Redmond, WA) and transferred to STATA 14 (College Station, TX) for analysis. The mean difference between the reference microphone and the iPods was calculated for each stimulus noise level for every combination of microphone and application. A difference of 0 dB would indicate perfect agreement between the iPods and the reference system, while a larger difference would indicate worse agreement between the iPods and SLM. In addition, a one-way Analysis of Variance (ANOVA) was used to determine if the three devices produced significantly different measurements. An ANOVA was also used to test if the microphone, application, and noise level had a significant impact on the difference in measurements between the reference system and the iPods. Tukey's HSD test was done post-hoc to determine if differences were observed between the different combinations of microphones and applications.

In the second experiment we evaluated whether external microphones could be used to reduce the variation of noise measurements between different models of smartphones using the same application. This has practical implications because as new smartphone models are released older models often become obsolete as the manufacturer discontinues updates and support for the older models. A student's t-test was used to compare the measurements of the reference system to the measurements made by the different devices. In addition, an ANOVA was used to compare the mean difference in noise measurements between the different devices using the same application and microphone. A significant difference between the different iOS devices would indicate that replacing a device's internal microphone with an external microphone does not improve the precision of the measurements across different generations of a device. However, if there is not a significant difference, it would suggest that external microphones can be used to help increase the precision of measurements across different generations of devices. Fifty-four measurements were collected for each combination of device, microphone, and application. In total 540 measurements were collected in experiment 2. All other parameters were identical to those used in experiment 1.

Results

Table 2-2 presents a summary of the mean difference calculations between the reference system and the iPods using several different application and iPods combinations. Across all three applications the iPod's internal microphone performed poorly. The NoiSee application could only measure up to 90 dBA using the built-in microphone. Both the iMM-6 and i436 microphones performed well when paired with the SoundMeter application, with only a 1 dB difference in sound level measurements when compared to the reference. Figure 2-1 provides a graphical summary of the distribution of differences in measurements stratified by application and microphone. The large interquartile range (IQR) for many of the combinations of applications and microphones suggests that only with particular configurations can a smart device be used to make reliable noise measurements.

Application	Microphone Type	Reference Noise Level (dBA) 60 [A]	65	70	75	80	85	90	95	100
NoiSee	Internal	7.1(0.9)	7.1(0.8)	7.1(0.8)	7.1(0.8)	7.2(0.8)	4.5(0.6)	0.1(0.6)	>LOQ	>LOQ
	iMM-6	-0.1(0.6)	-0.1(0.6)	-0.1(0.6)	-0.1(0.7)	0(0.6)	0(0.2)	-0.1(.2)	-0.7(0.2)	-4.3(0.3)
	i436	1.5(0.3)	1.3(0.3)	1.3(0.4)	1.3(0.3)	1.3(0.3)	1.5(0.3)	0.1(0.3)	0.2(0.3)	0(0.4)
SPLnFFT	Internal	2.1(1.0)	1.6(0.8)	1.6(0.8)	1.6(0.8)	1.6(0.8)	2.8(0.7)	1.5(2.9)	2.8(0.7)	2.7(0.7)
	iMM-6	1.1(0.7)	1(0.7)	1.1(0.8)	1.1(0.7)	1(0.7)	2.1(0.8)	1.6(2.2)	2.1(0.7)	2(0.7)
	i436	1.3(2.5)	1.2(2.2)	1.2(2.4)	1.2(2.3)	1.5(2.8)	2(2.8)	2.2(2.2)	2.3(2.4)	2.3(2.3)
SoundMeter	Internal	2.9(0.9)	3.2(0.8)	3.3(0.8)	3.3(0.8)	3.3(0.3)	3.4(0.3)	2.2(0.3)	3.3(0.3)	3.4(0.3)
	iMM-6	0(0.3)	-0.1(0.3)	0(0.3)	0(0.3)	0(0.3)	0(0.3)	0(0.3)	0(0.3)	0(0.3)
	i436	1(0.4)	0.9(0.4)	1(0.3)	1(0.4)	0.4(2.4)	0.9(0.4)	0.9(0.4)	0.9(0.4)	1(0.4)

Table 2-2 Mean differences and (standard deviation) between the iPods and sound level meter from experiment 1

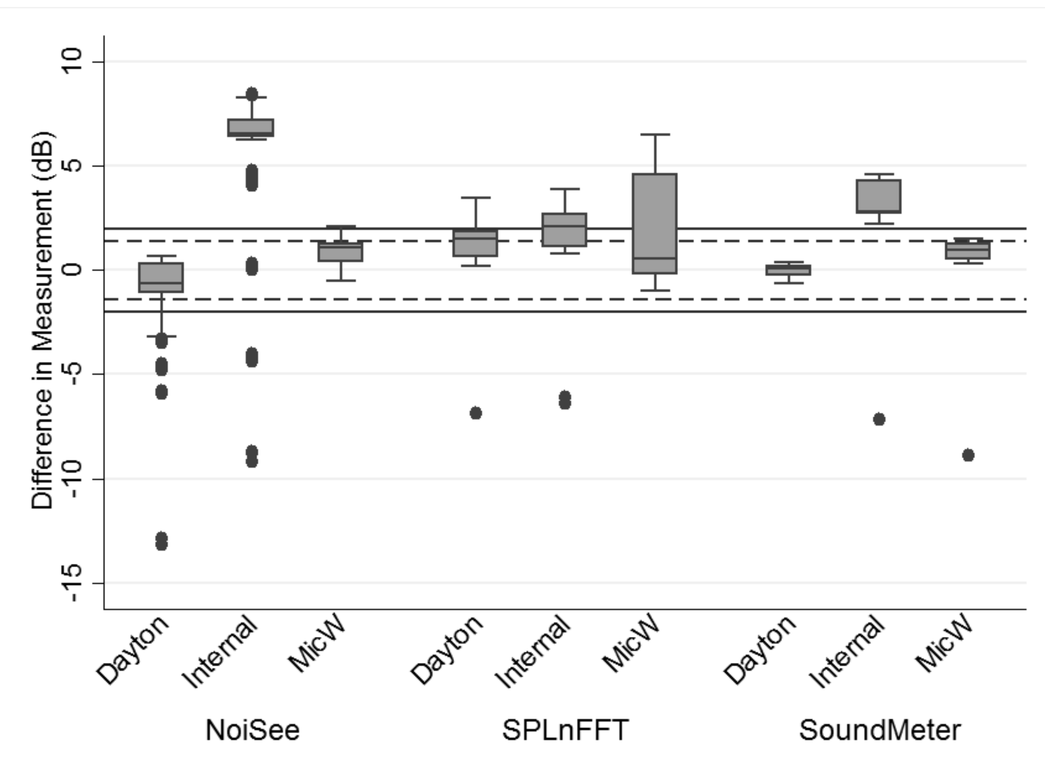


Figure 2-1 Difference in measurements between the iPods and SLM

The ANOVA (results not shown) comparing all the measurements made by the three iPods found that there was no significant difference in the measurements made by the three devices, even when stratified by the application and type of microphone that was used. This indicates that when the same types of devices use the same applications and microphones the results will likely be precise (i.e., small variability between devices), but not necessarily accurate (i.e., potentially large difference from the true noise level).

The results of the two-way ANOVA model examining the effect of the reference noise level, application, microphone, and the interaction between the application and microphone found that all terms in the model were highly significant ($p < 0.001$). This provides further support for the results in Figure 2-1 that shows certain combinations of applications and microphones perform better than others. The results also suggest that the accuracy of certain applications or microphones may differ across noise levels. The results are further complicated by the significant interaction term between the application and microphone; this means that microphones will perform differently depending on the application they are paired with.

The results from Tukey's pairwise comparison for the applications and microphones are presented in Table 2-3, which compares the mean difference between the different applications. The SoundMeter application had the lowest mean difference suggesting that it provide the most accurate noise measurements, followed by NoiSee and then SPLnFFT. While both NoiSee and SPLnFFT performed worse than the SoundMeter application, only SPLnFFT had a significantly larger mean difference. All three microphones were found to perform significantly different when compared to one another, with the best performance demonstrated by the iMM-6, then the i436, and then the internal microphone. Both the iMM-6 and i436 microphones, when calibrated, had a mean difference less than 2 dB, which is within the tolerance of a Type 2 sound level meter, suggesting that they may be appropriate to use for making accurate noise measurements. The results suggest that the internal microphone does not consistently provide measurements within the tolerance of a Type 2 sound level meter.

Application 1	Application 2	Mean 1 (dBA)	N 1	Mean 2 (dBA)	N 2	dif	HSD Test Statistic
NoiSee[A]	SPLnFFT	1.49	441	1.70	486	0.22	2.89
NoiSee	SoundMeter	1.49	441	1.35	486	0.13	1.63
SPLnFFT	SoundMeter	1.70	486	1.35	486	0.35	4.52[A]
Microphone 1	**Microphone 2**						
iMM-6	Internal	0.09	486	3.45	441	3.35	43.11[B]
iMM-6	i436	0.09	486	1.17	486	1.07	13.77[B]
Internal	i436	3.45	441	1.17	486	2.28	29.34[B]

[A] Because the Noisee app censored measurements >90 dBA those measurements were not included in this analysis.
[B] Indicates a significant ($p<0.05$) difference

Table 2-3 Tukey's multiple pairwise comparisons for the mean difference (dB) in measurements between different applications and microphones

The second experiment was designed to determine if an external microphone and application combination would allow different versions of a smartphone to make reliable measurements. Table 2-4 provides the mean difference, standard deviation, and sample size for each configuration tested. Across the different devices and using the internal microphone, the mean difference between the smartphone and reference system ranged from -1.09 to 24.99, with most of the configurations having a mean difference greater than 2 dB, which is outside the accuracy of a Type-2 instrument. When an external microphone was added all devices had a mean difference less than 1 dB. A student's t-test found that devices using the iMM-6 and i436 microphones did not have significantly different measurements than the reference (p= 0.8825 and p= 0.7610, respectively).

Device		Microphone iMM-6	Internal	i436
iPhone 4[A]	Mean		24.99	
	SD		0.12	
	N		54	
iPhone 4S	Mean	-0.11	-1.09	0.50
	SD	0.091	4.08	0.085
	N	54	54	54
iPhone 5S	Mean	0.02	1.76	0.82
	SD	0.08	1.39	0.082
	N	54	54	54
iPod 5G	Mean	-0.55	2.78	-0.01
	SD	0.09	0.16	0.07
	N	54	54	54

[A] The iPhone 4 was not compatible with the external microphones

Table 2-4 Mean difference (dB) between various smartphones configurations running the SoundMeter application, and the SLM

The results of the one-way ANOVA comparing the mean difference of all the devices running the SoundMeter application found that the difference between the devices to be highly significant ($p<0.0001$) in all cases. The results of a subsequent Tukey's multiple pairwise comparison between the different devices are presented in table 2-5. Only the 5th generation iPod and iPhone were found to not have significantly different mean differences.

Device 1[A]	Device 2	Mean 1	Mean 2	Difference	HSD Test Statistic
iPhone 4	iPhone 4s	17.01	0.21	16.80	133.10[C]
	iPhone 5s	17.01	1.08	15.94	126.25[C]
	iPod 5G	17.01	1.35	15.67	124.09[C]
iPhone 4s	iPhone 5s	0.21	1.08	0.87	6.86[C]
	iPod 5G	0.21	1.35	1.14	9.01[C]
iPhone 5s	iPod 5G	1.08	1.35	0.27	2.15

[A] N = 54 for each microphone [B] All devices were running the SoundMeter application
[C] Indicates a significant ($p<0.05$) difference

Table 2-5 Tukey's multiple pairwise comparisons for the mean difference in measurements between the different devices and SLM

Discussion

The results from experiment 1 indicate that it is possible to use different iOS smart devices to make accurate noise measurements under certain conditions. However as Table 2-5 shows, the internal microphones on the devices tested are not able to make noise measurements within 2 dB of a reference noise level, which indicates that the internal microphone is not equivalent to a microphone on a Type-2 SLM. This is not surprising, as the internal microphones were designed to only capture a person's voice with sufficient accuracy to communicate information, and not to perform sound level measurements. In addition, when using the NoiSee application with the internal microphone it appears that the application will clip measurements at 90 dBA, effectively limiting the measurement range of this device/application combination. This limits the usefulness of the application as both a SLM and a dosimeter for use in high noise occupational or recreational settings. Based on the results, it appears that smartphone applications measuring noise with the internal microphone should not be used in assessing personal noise exposures.

Our results suggest that an external microphone and source of calibration are needed to make sufficiently accurate noise measurements. This somewhat increases the costs of using smartphones to make noise measurements. However, these microphones are relatively cheap in comparison to the cost of a smart device; the iMM-6 costs approximately $20 while the i436 costs approximately $130. The need for calibration is a larger issue, but calibrators can also be purchased at a relatively small cost. For those without calibration equipment, several applications have pre-defined profiles for certain microphones. However, there has been no evaluation as to the accuracy of using these pre-defined profiles. Additionally, the microphone manufacturer may provide the microphone's sensitivity which can be entered into the application to crudely calibrate the measured levels. Again, there has been no formal investigation in to the accuracy of the measurements using this method, so the results should be interpreted with caution.

Despite the additional technical challenges of using an external microphone the results presented in Table 2-2 and Figure 2-1 indicate that using external microphones is crucial for accuracy. Although the results in Table 2-4 indicate that the iMM-6 microphone performed significantly better than the i436 microphone, both microphones had a mean difference less than 2 dB when compared to the Type-1 SLM. Additionally, the results from experiment 2 show that these microphones may potentially allow different generations of devices to make accurate noise measurements when running the same application. The results of the t-test indicated that the measurements made by devices using either the iMM-6 or i436 external microphones did not differ significantly from the Type-1 SLM. However, as the results from the ANOVA and Tukey's multiple pairwise comparison tests indicates there is still a significant difference between different devices using the same microphone and application. This indicates that the different generations of smartphones may give accurate results (i.e. within 2.0 dBA of a reference level) but the measurements may be significantly different between different devices.

Another complicating factor in using smartphones to perform noise measurements is the selection of an application. The 3 applications evaluated in this experiment were chosen based on the results from Kardous and Shaw (2014).[20] Based on the results in Table 2-2 & Table 2-4 the SoundMeter application performed better than the other two applications. However, it is important to consider that between 2013 and 2015 Apple has gone from the 8th to the 9th iteration of iOS, and additional applications may have been added, removed, or updated in the iTunes application store. For instance, NoiSee has not been updated since 2012. The speed at which applications and software change makes it difficult to say with absolute certainty which application will provide the most accurate measurements. However, the fact that the developer of the SoundMeter application produces other products in addition to the smartphone application makes it likely that the application will continue to be supported in the near future.

Several studies have examined the accuracy of various smartphone applications to measure noise. However, these studies have only evaluated the accuracy of internal microphones. The results from this experiment again demonstrate that generally the internal microphone should not be relied on to make accurate noise measurements.[20,69,73] The only exception has been found by Murphy et al. (2016), who reported that the Sound Level Analyzer Lite (SLA Lite) application for iOS had a mean difference ranging from -0.76 to 0.57 dB.[74] This is encouraging because using the device's internal microphone reduces technical and logistical barriers to making accurate measurements and more closely emulates how a typical layperson would use their smart device. However, Murphy et al. (2016) also noted that the accuracy of smart devices varied widely, especially for devices running the Android operating system. As demonstrated here, using external microphones greatly reduces the variation of the measurements in different generations of iOS devices. It is possible that using an external microphone can also increase the accuracy and reduce the variability of measurements made by Android devices, but this has not yet been evaluated.

It is also worth noting that Murphy et al. (2016) was examining the accuracy of smart devices for general environmental noise measurements. In this context it is logical to assume that the increased variability from using the device's internal microphone is less important because of the potential to collect hundreds or thousands of measurements, but a systematic bias in measurements can still result in erroneous measurements. However, in instances where a large number of samples cannot be collected the large measurement variability can drastically impact the exposure estimate. This is especially true in the workplace where samples sizes are typically much smaller, and where overestimation of exposures can lead to the implementation of costly controls, while underestimation of exposures can result in workers not being adequately protected from hazardous noise exposure.

Conclusions

This study expands on previous studies by evaluating applications that were previously identified to be the most accurate in conjunction with inexpensive external microphones. The use of these external microphones dramatically increased the accuracy and precision of the measurements made by the smart devices that were evaluated. The results presented here were from measurements made in a continuous noise environment. Further studies should be conducted looking at the performance of smartphones in calculating noise dose in an environment with intermittent or rapidly changing noise. Despite the technical challenges that were discussed, the results of this study indicate that in certain situations smartphones running the correct application and equipped with an external calibrated microphone can collect noise measurements within 2.0 dBA of a type 1 SLM which is roughly just as accurately as a Type-2 SLM. It is very unlikely that smartphones will be used for compliance measurements in the near future. However, smartphones have significant value as survey tools, and as SLMs in low resource areas. In addition, these devices can be used to map environmental noise in a community by utilizing a smartphone's GPS function.[75,68,76,67] Finally, as sensor technology improves it may be possible to collect data on multiple physical hazards at once by using the smartphone as the device that stores and exports the data from the sensors.

Chapter 3 – Using Smart Devices to Measure Intermittent Noise in the Workplace

Abstract

Smart devices (phones, tablets, etc.) are becoming more common in the workplace. Previous research has shown that these devices can potentially provide accurate noise measurements when exposed to continuous noise. This study attempts to determine if smart devices can provide accurate noise measurements when exposed to varying noise in the workplace. In experiment 1, four iPods were each paired with a Larson Davis Spark dosimeter and exposed to randomly fluctuating pink noise in a reverberant sound chamber. Descriptive statistics and the mean difference between the iPod and its paired dosimeter were calculated for the 1-second data logged measurements. The calculated time weighted average (TWA) was also compared between devices. In experiment 2, 15 maintenance workers and 14 office workers wore an iPod and dosimeter during their work shift for a maximum of 5 work days. A mixed effects linear regression model was used to control for repeated measures and to determine the effect of the device type on the on the projected 8-hour TWA. In experiment 1 a total 315,306 1-second data logged measurements were made. The interquartile range of the mean difference fell within +/- 2.0 dBA which is the standard used by the American National Standards Institute to classify a type 2 sound level meter. The mean difference of the calculated TWA was within +/- 0.5 dBA except for one outlier. In experiment 2, the results of the mixed effects model found that, on average, iPods measured an 8-hour TWA 1.7 dBA higher than their paired dosimeters.

This study shows that in some instances iPods have the ability to make reasonably accurate noise measurements in the workplace, but they are not as accurate as traditional noise dosimeters.

Introduction

Hearing loss is the third most common chronic condition in the United States and noise induced hearing loss (NIHL) is the most common work related illness [9]. Noise is the single greatest preventable cause of hearing loss and one of the most common occupational hazards.[77] The National Institute of Occupational Safety and Health (NIOSH) estimates that over 22 million American workers are exposed to hazardous noise >85 A-weighted decibels (dBA).[16] NIHL prevalence can vary widely depending on the industry. Workers in traditionally noisy industries (mining, construction, manufacturing and transportation) have a prevalence of NIHL ranging from 9.5 to 34.8%, and in these industries there is considerable information available regarding noise exposures.[78] There is much less information about noise exposure available in the service industry, healthcare, and the wholesale and retail trade despite a prevalence of any hearing impairment ranging from 7.8 to 16.7%, i.e., not much below that of industries traditionally perceived as “noisy”.[78] Many companies in these industry sectors do not have formal occupational health departments that can monitor a worker’s exposure to noise.

Collecting exposure information in these industries requires the use of noise dosimeters or sound level meters, which are expensive and require trained individuals to operate and interpret the results. By contrast, smart devices (phones, tablets, and other devices) have the ability to utilize applications (“apps”) that can make noise measurements in a very straightforward and simple manner. A study by Nast et al. in 2014 found that the measurements made by a variety of apps on an iPhone 4S were subject to significant error and were considered unsuitable to measure noise.[69] However, a laboratory study conducted by Kardous and Shaw in

2014 tested 10 Apple iOS and four Android apps and found that four iOS apps had a mean difference within 2.0 dBA of a reference sound.[20] The authors also found that different generations of Apple products had varying levels of accuracy in measuring noise. Another laboratory study by Murphy and King in 2016 found that iOS apps were generally superior to Android apps, but that the app used, phone model, and age of the device could all affect the measurement accuracy.[74] We conducted a study in 2016 that examined the effect of several commercially available microphones, the MicW i436 and the Dayton Audio iMM-6, on the accuracy of noise measurements in reverberant sound chamber. Using a similar method to Kardous and Shaw (2014) measurements were taken using different generations of iOS devices running three different apps while using the external microphones. We found that both external microphones substantially increased the accuracy and precision of noise measurements and reduced the measurement variability introduced by different iOS devices and apps.[79]

All of the previous studies were conducted in a controlled laboratory setting and were focused on assessing the accuracy of smart devices when measuring steady state (i.e., non time-varying) noise. However, in the workplace such stable exposure conditions are uncommon. In addition, most of the contemporary noise measurements apps have the ability to datalog and integrate a noise dose over a workday, but such measurements have never been compared to measurements from traditional noise dosimeters. This study aimed to address these knowledge gaps in two ways. The first (experiment 1) was to determine how accurately smart devices measured intermittent noise in a laboratory setting by comparing measurements made by a noise dosimeter to those made by smart devices. The second (experiment 2) was to compare the real-world accuracy of smart device noise measurements to those made with noise dosimeters in two worker populations with different exposure profiles.

Methods

For experiment 1 a 4-hour sample of random pink noise was generated in MATLAB version 8.5 (Natick, MA) using the "Pink Noise Generation with MATLAB Implementation" software package (Hristo Zhivomirov 2013). The noise was exported as a .wav file and loaded in to the REATPLus software (ViAcoustics, Austin, TX) and transduced through three JBL XRX715 two-way loud speakers inside a reverberant sound chamber located at the NIOSH acoustic testing laboratory in Cincinnati, OH (see Figure 3-1 for an example of the equipment used).[79] The reverberant sound chamber allowed for the generation of a sound field with equal energy throughout the chamber, which negated the influence of microphone location on the noise measurement.

Figure 3-1 The paired dosimeters and devices mounted on a stand in the reverberant sound chamber prior to testing in experiment 1

Noise was measured using four Spark Model 706 dosimeters (Larson Davis, Depew, NY), each of which was paired with a 5th generation iPod (Apple, Cupertino, CA) running iOS version 9.3.2 with the SoundMeter app (Faber Acoustical, LLC) and a MicW i436 external microphone (Beijing, China). The application and microphone were chosen because they provided the most accurate measurements in our previous study.[79] In addition, the MicW i436 claims that it meets the International Electrotechnical Commission's (IEC) standard for a class 2 microphone.[71,72] The clocks on all of the instruments were synchronized, and each pair of devices was started at the same time and set to log noise measurements at 1-second intervals for the duration of the experiment. Both the dosimeter and the iPod were set with a threshold of 40 dB, exchange rate (ER) of 3 dB, and a criterion level of 85 dB. This was done to ensure that the full range of noise levels presented in the chamber was integrated into the noise dose measured by both devices. All of the devices were calibrated at 114 dB using a Larson Davis Cal 150B SLM calibrator before and after the experiment. Each pair of devices was exposed to random pink noise for between 15 and 240 minutes over 11 different trials; this allowed for evaluation of effects of different runtimes on agreement of the paired devices. Because this experiment was comparing paired devices the results from all the trials were combined into one dataset for analysis. Descriptive statistics and the mean difference were calculated for each device pair for both the 1-sec data logged measurements and the time-weighted average (TWA) calculated for each measurement by both devices.

Experiment 2, which involved human participants, was approved by the institutional review board at the University of Michigan (HUM00100764). Fifteen volunteer maintenance workers at the University of Michigan were recruited and provided informed consent to participate in the study. The maintenance workers were chosen because we believed that they would be exposed to high levels of intermittent noise given their work activities. Each was followed for a maximum of five consecutive work days. Fourteen volunteer office workers at the university with no occupational noise exposure were also recruited and followed for a maximum of five consecutive workdays. During their work-shifts, which were all 8-hours in duration, all workers wore a 3M Edge eg-5 (3M, Maplewood, MN) and a 5th generation Apple iPod Touch inside a protective case running iOS version 9.3.2 with the SoundMeter app, and connected to a MicW i436 external microphone. The microphones for both devices were placed side-by-side on the dominant hand shoulder of the participant (see Figure 3-2 for an example) for the duration of each measured work-shift. In the event that the iPod failed to record a measurement the paired dosimeter measurement was also excluded from the analysis.

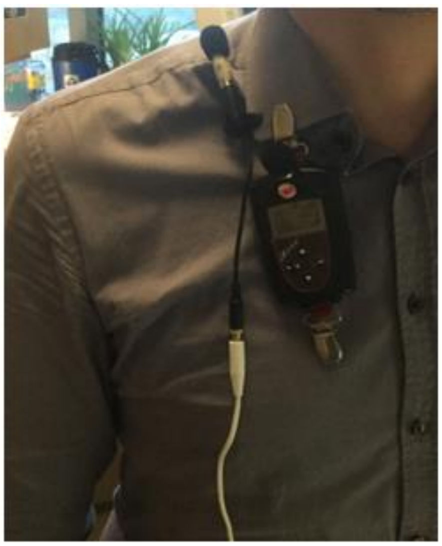


Figure 3-2 An example the noise dosimeter and iPhone microphone placed on a worker in experiment 2

Both the dosimeter and smart device were set to measure noise using the method specified by NIOSH with an exchange rate of 3 dB, criterion level of 85dB, and a threshold of 80 dB [16]. All devices were pre and post calibrated at 1000Hz and 114 dB using a Larson Davis Cal 150B SLM calibrator before and after data collection. Measurements from devices with a post calibration <113.5 and >114.5 dB were excluded. The exposure profiles of all workers were visually examined using the 3M Detection Management Software (3M, Maplewood, MN).

Descriptive statistics were calculated for the 8-hour TWA for each group of workers in STATA 14 (College Station, TX). A mixed effects linear regression model was developed to compare the difference in measurements between the dosimeter and smart device while accounting for repeated measurements. This model is displayed in Equation 1, where Y_{it} indicates the 8-hour TWA for subject i at time t, β_1 and $\beta_2$are indicator variables for what type of device was used and from which group the worker came, $b_i$is the random intercept for the worker and b_{it} is the random intercept for day nested in the worker.

Equation 1.

$$Y_{it} = \alpha + \beta_1(device) + \beta_2(group) + b_i + b_{it} + \varepsilon_i$$

Results

Table 3-1 presents a summary of the measurements made by each device in experiment 1. On average each device made 39,413 measurements across all the trials. Measured noise levels ranged between 34.8 to 98.0 dBA with a mean of 75.0 dBA and a standard deviation of 4.5 dBA. The difference in 1-second data logged measurements for each pair of devices is displayed in Figure 3-3. A value of 0 indicates perfect agreement between the devices while values further away from 0 indicate less agreement. The inter-quartile range (IQR) of the differences between the iPod and dosimeter fall within or very close to the +/- 2.0 dBA range which is the criteria used by the American National Standards Institute (ANSI) to classify type-2 microphones.[17] However, there were numerous outlier measurements that were outside the +/- 2.0 dBA range. Similarly, Figure 3-4 shows that the difference in the calculated 8-hour TWA between the dosimeter and iPod pairs is typically +/- 0.5 dB, with the exception of one outlier. Figure 3-4 also suggests that the iPods tend to produce measurements that are slightly higher than the dosimeters.

	Mean	SD	Min	Max	Avg. N	Total N
Total	75.0	4.5	34.8	98.0	28,664	315,306
Pair 1						
iPod	74.7	4.9	35.7	88.9	3,585	39,430
Dosimeter	74.9	4.1	37.1	88.3	3,585	39,430
Pair 2						
iPod	75.7	5.0	34.8	89.5	3,582	39,400
Dosimeter	75.8	3.9	40.4	87.6	3,582	39,400
Pair 3						
iPod	74.8	4.8	36.6	89.3	3,583	39,409
Dosimeter	75.1	4.2	36.6	98.0	3,583	39,409
Pair 4						
iPod	74.5	4.8	36.4	90.2	3,583	39,414
Dosimeter	74.6	4.0	37.9	88.1	3,583	39,414

Note: There were a total of 11 trials conducted for each pair in experiment 1.

Table 3-1 Summary statistics for noise exposure (in dBA) for experiment 1

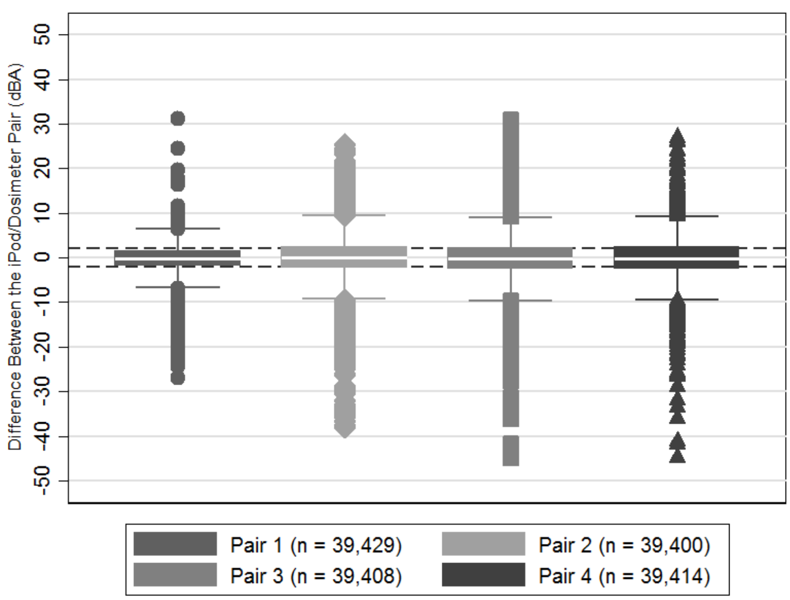


Figure 3-3 Difference in 1-second logged measurements for each pair of devices from experiment. The dashed line represents +/- 2 dBA respectively

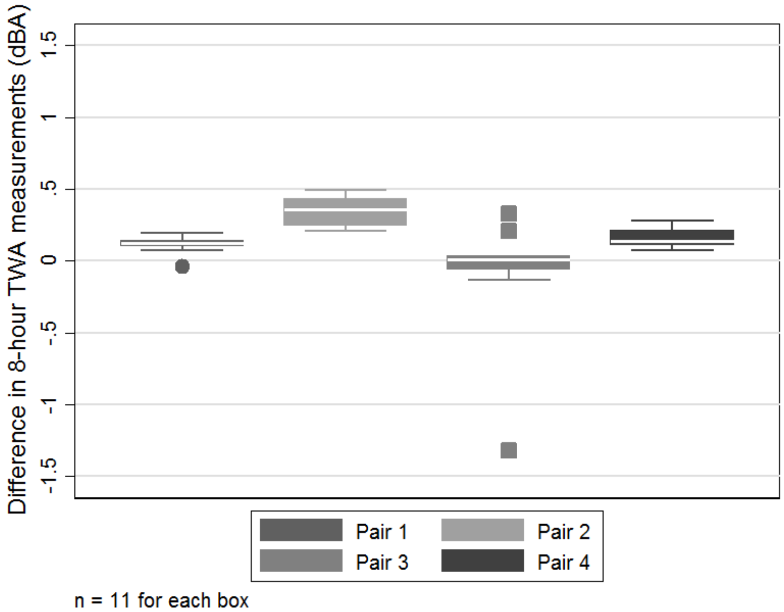


Figure 3-4 Difference between the 8-hour TWA for each dosimeter/iPod pair from experiment 1

Descriptive statistics for both occupational groups are presented in Table 3-2. A total of 54 iPod and dosimeter measurements were collected from the maintenance workers while 50 iPod and dosimeter measurements were collected from the office workers. The results from the first day of monitoring the maintenance workers were discarded because of widespread failure of the iPods due to a lack of protective cases. This resulted in only four days of data from the maintenance workers cohort. Despite the fact the office worker cohort was monitored for an additional day (i.e., 5 days vs. 4), many of the office workers had work obligations that required them to miss a day or more of the study. This resulted in the office worker cohort having fewer samples than the maintenance workers. As would be expected, the maintenance workers had on average higher levels of noise exposure compared to the office workers. However, office workers had a larger standard deviation, suggesting that there is a greater variability in the 8-hour TWA measurements for the office workers than the maintenance workers. For both groups of workers the iPods on average produced higher measurements than the noise dosimeters. Table 3-3. shows that the mean difference between the measurements made by the dosimeters and the iPods ranged between -0.2 and -4.4 dBA for the maintenance workers and -1.6 to 0.6 dBA for the office workers, depending on the measurement day.

		Device	
Occupational Group		iPod	Dosimeter
Maintenance Workers	N	54	54
	Mean	84.1	81.6
	SD	5.5	6.3
Office Workers	N	50	50
	Mean	65.9	65.2
	SD	9.6	9.2

Table 3-2 Descriptive statistics for experiment 2, 8-hour TWA noise measurements (dBA) made using an iPod and noise dosimeter

		Day					Total
Group		**1**[a]	**2**	**3**	**4**	**5**	
Maintenance Workers	Mean		-3.8	-4.4	-0.2	-1.5	-2.5
	SD		7.7	9.6	2.8	2.3	6.4
	N		12	14	13	15	54
Office Workers	Mean	-0.3	-0.9	0.6	-1.6	-1.3	-0.7
	SD	2.4	6.7	4.2	2.5	4.4	4.4
	N	7	11	11	10	11	50

[a] Day 1 measurements were not included because of widespread failure of the iPods.

Table 3-3 Mean difference in Experiment 2 between the 8-hour TWA measurements (dBA) made by the iPod and dosimeter

Results from the mixed effects regression model are presented in Table 3-4. By including a random intercept for each participant and each day nested within participant the measurements from the iPod and dosimeter are centered for each person and day. This made it possible to determine that the iPods systematically measured noise exposure 1.7 dBA higher than the noise dosimeters. On average noise exposure for the maintenance workers was 22.8 dBA higher than the office workers. Approximately 76.9% of the variance in the model was explained by the random effect for worker and day nested within worker. This implies that only 23.1% of the variance between measurements made by the iPods and dosimeters could not be explained by the model.

Fixed Effects	Coefficient (dBA)	SE	P-value	95% CI (dBA)	
Intercept	86.4	1.6	<0.001	83.3	89.5
Device[a]	-1.7	0.6	0.004	-2.9	-0.6
Group[b]	-22.8	1.7	<0.001	-26.0	-19.5
Random Effects	**Estimate**	**SE**			
Subject: Random Intercept	40.3	14.7		19.7	82.5
Day: Random Intercept	16.2	4.4		9.5	27.6
Residual	16.9	2.4		12.8	22.3

[a] 0 = iPod, 1 = dosimeter
[b] 0 = maintenance workers, 1 = office workers

Table 3-4 Fixed and random effects for the mixed effects linear regression model for Experiment 2

Discussion

We have successfully evaluated the performance of smart devices used to measure intermittent noise exposures in comparison to gold-standard measurement instruments. The results from experiment 1 add to the growing body of evidence that low cost external microphones can be used by a smart device to collect noise measurements that approach the accuracy of conventional instruments. The median for the difference between 1-second logged measurements was close to 0 dBA for all the pairs of devices (Figure 3-3). However, there are a number of measurements in which the difference in measurements between the two devices is > 2.0 dBA. Each pair of devices was started manually; while care was taken to start and stop the measurements at the same time, it is likely that each dosimeter/iPod pair was recording slightly different 1-second intervals, which may account for some differences. Traditional noise dosimeters are built for a singular purpose while even factory-new iPods in so-called "airplane mode" (i.e., with communication functions disabled) are running numerous processes that could impact the performance of the application recording noise measurements. We had no way to detect or account for this possible difference during our analysis. Despite these potential sources of error, Figure 3-4 shows that the 8-hour TWA calculated by the iPods was generally within 0.5 dB of the TWA calculated by the matched dosimeters. Previous studies have shown that smart devices can make very accurate measurements when exposed to continuous noise and compared to results from a sound level meter.[20,79] However, this is the first study that examined the accuracy of smart devices in measuring intermittent noise and compared the calculated 8-hour TWA to results from a noise dosimeter.

Experiment 2 represented a field test of smart devices to determine how well they performed in a "real world" scenario and determine how durable the devices were in the workplace. The two occupational groups were chosen because we expected them to have dissimilar exposure profiles. As shown in Table 3-1, maintenance workers were indeed exposed to higher levels of noise, though the office workers had a larger standard deviation in their mean 8-hour TWAs. The mean difference in 8-hour TWAs between smart devices and noise dosimeters was smaller for office workers than for maintenance workers (Table 3-2). This is likely due to the fact that office workers are not routinely exposed to levels of noise that exceed the threshold setting on the dosimeter. This was to be expected and suggests that the smart devices are not incorrectly measuring sub-threshold noise as above the threshold, which would contribute to an artificial increase in a worker's 8-hour TWA. Unlike office workers, maintenance workers were regularly exposed to noise levels exceeding the threshold setting of the devices. Visual examination of the graphical output from the dosimeter software indicated that the maintenance workers were generally exposed to more rapidly fluctuating levels of noise than the office workers, which likely also contributed in the lower agreement between the dosimeters and iPods. This suggests that smart device apps may be less accurate in measuring rapidly fluctuating noise levels and should not be used to measure peak or maximum noise levels.

Using a mixed effects linear regression model we were able to account for the repeated measure design of this study and to evaluate the systematic difference in measurements made by the iPods compared to the traditional noise dosimeters. Overall, the iPod produced an 8-hour TWA that was 1.7 dBA higher than the noise dosimeter with a standard error of 0.6 dBA. While the overall mean difference falls within the 2 dB tolerance limit ANSI uses to define a type 2 SLM, when the model was run stratified by occupational group the iPod produced an 8-hour TWA that was 2.6 and 0.7 dBA higher than a dosimeter in the maintenance and office workers, respectively. This suggests that smart devices should not be used in place of dosimeters for compliance measurements, especially for workers who are exposed to variable levels of noise throughout the workday. Therefore, these results should not be interpreted as an indication that smart devices with an external microphone are equivalent to a type-2 SLM. It is also important to consider that there are a large number of noise measurement apps available. This study only used one app (SoundMeter) based on previous data that showed this app performed the better than several other apps that were available.[20] It is unknown how well other apps would perform because they have not been evaluated to the same extent that SoundMeter was here in our previous study or in Kardous and Shaw (2014).[20,79] Additionally, there many other models of external microphones available however, there has been little research done on the quality of these microphones

In addition to the quantitative results, we were able to make several observations about the durability and the feasibility of using smart devices to measure noise in the workplace. The first observation is that many smart devices will automatically turn off when exposed to temperatures that exceed the devices' safe operating parameters. When this happens the noise measurement app is closed and no measurements are made. Additionally, using an external microphone necessitates attaching the microphone to a 3.5mm extension cord so that the microphone can be mounted in the hearing zone of the measured subject while the smart device is placed in a pocket. The smart device could theoretically be mounted in a worker's hearing zone, but the design and fragility of smart devices makes this infeasible in practice. If the external microphone is disconnected from the device the app will either stop recording measurements or continue recording measurements using the internal microphone, which has been found to be highly inaccurate in some cases.[20,79] This occurred during the first day of sampling the maintenance workers and resulted in the discarding of all of the first day's measurements. This issue was resolved by purchasing several protective cases for the iPods. Among office workers, it can be difficult for a person without pockets to wear an iPod for their entire work shift. This can be alleviated by using armbands to mount the device and using a short 3.5 mm extension cord to mount the microphone in the hearing zone.

Conclusions

Despite these drawbacks, we have shown that commercially available iOS apps paired with an external microphone can make reasonably accurate full-shift noise measurements. The high prevalence of smart phone use in the United States and around the world means that with an external microphone and app it is possible for lay individuals to make accurate noise level measurements at work or in the general environment.[22,66] While smart devices and apps are not accurate enough to replace traditional noise dosimeters at this time, they do have the potential to reduce the cost and difficulty of identifying worker who need further monitoring or should be enrolled in a hearing protection program, particularly in industries with limited occupational health and safety resources. These devices can also empower workers to make their own measurements and lobby their employer for additional noise monitoring or the implementation of noise controls. In situations where traditional noise dosimeters are not available, such as small businesses, smart devices can be used to gather reliable noise exposure data. The quality of the collected data is still dependent on the user, making it imperative that these apps provide some basic measurement instructions on how to effectively collect noise measurements. However, the use of smart devices provides an opportunity for workers and occupational health professions to better characterize noise exposure in the workplace that can then be used to make decisions on how to best protect a worker’s hearing.

Chapter 4 - Imputation of Missing Values in a Large Job Exposure Matrix Using Hierarchical Information

Abstract

Job exposure matrices (JEMs) represent a useful and efficient approach to estimating occupational exposures. This study uses a large dataset of full-shift measurements and employs imputation strategies to develop noise exposure estimates for almost all broad level standard occupational classification (SOC) groups in the US. The JEM was constructed using 748,598 measurements from the government, private industry and the published industry. Imputation was used to take advantage of the hierarchical structure of the SOCs and the mean occupational noise exposures were estimated for all broad level SOCs, except those in major group 23-0000 (Legal Occupations), for which no data were available. The estimated posterior mean for all broad SOCs was found to be 82.1 dBA with within- and between-major SOC variabilities of 22.1 and 13.8, respectively. Of the 443 broad SOCs, 85 were found to have an estimated mean exposure >85 dBA while 10 were >90 dBA. By taking advantage of the size and structure of the dataset we were able to employ imputation techniques to estimate mean levels of noise exposure for nearly all SOCs in the US. Possible sources of errors in the estimates include misclassification of job titles due to limited data, temporal variations that were not accounted for, and variation in exposures within the same SOC. Our efforts have resulted in an almost completely-populated noise JEM that provides a valuable tool for the assessment of occupational exposures to noise. Imputation techniques can lead to maximal use of available information that may be incomplete.

Introduction

Noise induced hearing loss (NIHL) is the most common workplace injury, affecting an estimated 11.4% of workers in the United States.[78] While it is difficult to quantify the economic costs of NIHL, the US Veterans Administration reported direct costs of $1.2 billion in 2006 on hearing disability and tinnitus in addition to $288 million spent annually by the Veterans Administration on hearing aids.[80,81] More recently, we have estimated the direct and indirect costs of preventable NIHL to be between $58 and $152 billion annually in the US, with a central estimate of $123 billion per year.[13] Thus is reasonable to assume that NIHL has a substantial and underappreciated ongoing impact on the US economy. Despite the clear relationship between hazardous noise exposure (>85 dBA) and hearing loss it is estimated that more than 22 million US workers are exposed to hazardous levels of noise at work.[6,16]

While it is well-established that hazardous noise exposure causes NIHL, conducting occupational epidemiological studies to further elucidate and quantify this relationship is challenging. Ideally, prospective cohort studies would be implemented to follow workers and monitor their noise exposure for a decade or more until the onset of significant NIHL. However, the costs and time required to conduct a longitudinal study make this approach difficult and rare. Typically, researchers instead rely on retrospective cohort studies to assess the relationship between an occupational exposure and a disease.[82] In these retrospective studies it can be difficult to develop to accurately estimate exposures.[83] To overcome these difficulties researchers have increasingly relied on job exposure matrices (JEMs) to retrospectively assess occupational exposures.[82,84–88]

In its most basic form a JEM consists of two axes: one axis contains a list of jobs or job descriptions, and the other contains qualitative or quantitative information about the magnitude and/or prevalence an exposure.[82] A JEM can be further refined by adding further information on specific job tasks, and the time period of exposure. The main advantage of a JEM is that it allows the use of previously collected industrial hygiene measurement records that greatly simplify epidemiological exposure assessment. A JEM also makes it possible to identify occupations and industries that have high levels of an exposure so that targeted controls can be implemented to reduce potential exposures.

There are many issues that arise when using a JEM as an exposure assessment tool. The first is that exposure varies depending on both a worker's job title and the industry that the worker is employed in.[63] Workers with similar job titles can have large differences in their exposures depending on the industry they are employed in. It has also been shown that the majority of purportedly homogeneously exposed groups (HEGs) of workers – often based on job title – in the same workplace had more than a 2-fold difference in exposures.[89] The second issue is that exposure typically vary over time for a worker in the same job as changes in their workplace lead to a change in exposure patterns.[82,89] Finally, data scarcity often necessitates the use of qualitative exposure measures, which reduce the statistical power of a JEM to detect an exposure-response relationship.[90]

The JEM we describe here consists of 748,598 full-shift occupational noise measurements made according to the Occupational Safety and Health Administration's (OSHA) Permissible Exposure Limit (PEL) for noise.[14] Our previous meta-analysis of a subset of 715,867 measurements included in this JEM found that 26.4% of 235 job titles had no heterogeneity across sources (literature, government and industry reported sources), while 63.0% of job titles were found to have moderate to high levels of heterogeneity.[91] Despite the size and scope of this JEM, many job titles still lack exposure information. The goal of this present study is to take advantage of the hierarchical structure of the job title system used in this JEM in order to develop imputation strategies to calculate estimates of exposure and variability for job titles in which no exposure information is available and then determine which job titles have an estimated exposure greater than the current OSHA action level (AL) of 85 dBA and PEL of 90 dBA.

Methods

The JEM was constructed using OSHA[14] and Mine Safety and Health Administration (MSHA)[92] PEL measurements (i.e. a 90 dBA criterion level and threshold, and 5 dB time-intensity exchange rate) from government databases maintained by OSHA and MSHA, measurements from the published literature, and measurements submitted by private industry. Details about the data cleaning process for the JEM have been described elsewhere.[91,93] Briefly, data was received from the various sources in an electronic format, typically a Microsoft Excel file (Redmond, WA). The data was imported in to STATA 14 (College Station, TX) for data cleaning. Industry information was first coded using the 2012 North American Industrial Classification System (NAICS) from the US Census Bureau.[94] Using information on the industry of employment and job titles from the various government agencies, companies, and published literature from which measurement data were drawn, each measurement was assigned a job title using the Bureau of Labor Statistics' 2010 Standard Occupational Classification (SOC).[95]

The SOC structure is hierarchical and made up of major, minor, broad, and detailed groups. Figure 4-1 provides an example of this structure using the detailed SOC 33-9099 which corresponds to the SOC group of "Protective Service Workers, All Other" and is nested in the broad SOC 33-9090, "Miscellaneous Protective Service Workers". The broad SOC is in turn nested in the minor SOC 33-9000, "Other Protective Service Workers," which resides within the major SOC 33-0000,"Protective Service Occupations".

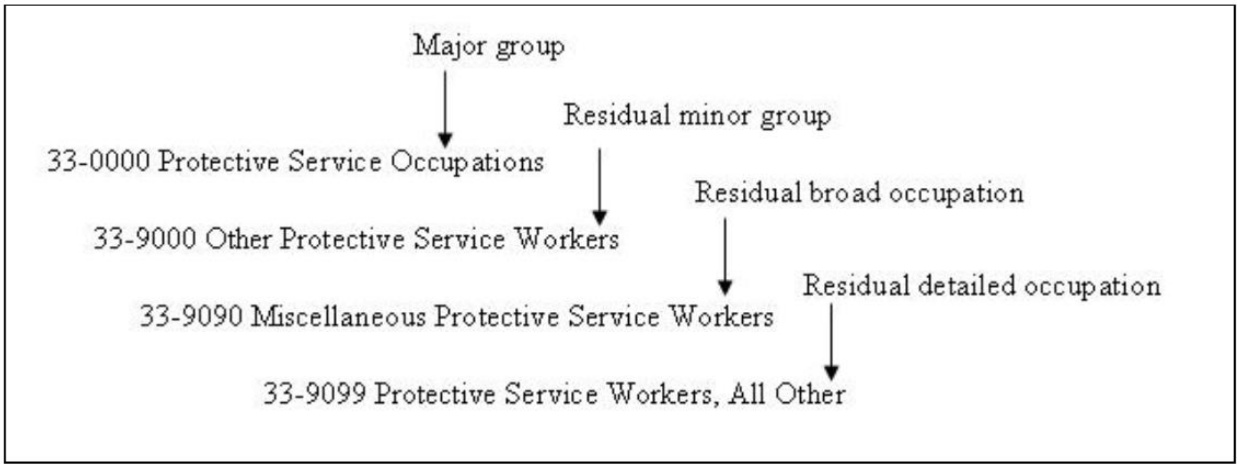


Figure 4-1 Example of the hierarchical structure in the SOC system reprinted from the 2010 SOC User Guide (Bureau of Labor Statistics 2010)

To take advantage of the hierarchical structure of the SOC system we chose to use a parametric Bayes imputation method to impute missing values at the broad SOC level. All models were performed in R. There were a total of 461 broad SOCs, 222 (48%) of which had missing data. Of these 222 broad SOCs four were in the major SOC group 23-0000 (Legal Occupations). Because we did not have any measurements for this occupational group we could not perform any imputation; imputation was possible for all other broad SOCs. We first created training and validation datasets to evaluate imputation accuracy by comparing observed and imputed data in the validation dataset in order to benchmark our imputation against the truth. We then used the full dataset to impute missing values for each broad SOC to be used for future research.

Model Construction and Validation

A hierarchical model was used to estimate missing values in the dataset. The derivation of the method used is presented in Appendix 1. Let *i* denote the index of major SOCs and let *j* denote the index of broad SOCs that are nested within the major SOCs. There are two data components in this model: the observed SOCs and the missing SOCs. We assign separate indices for these two data components. For those broad SOCs that are observed, Y_{ij}^{obs} is the sample mean of the *j*th broad SOC in the *i*th major SOC. Consider a model describing our information about a hierarchical dataset $\{Y_1^{obs}, \ldots, Y_I^{obs}\}$ where $Y_i^{obs} = \{Y_{i1}^{obs}, \ldots, Y_{in_i}^{obs}\}$ consisting of all the observed data in the *i*th major SOC. s_{ij}^{obs} and n_{ij}^{obs} are the corresponding sample standard deviation and sample size, respectively, corresponding to the *j*th broad SOC nested in the *i*th major SOC. All that is known about this dataset are Y_{ij}^{obs}, s_{ij}^{obs} and n_{ij}^{obs} and the hierarchical structure of the dataset. θ_{ij}^{obs} is the true (unknown) mean of *j*th observed broad SOC in the *i*th major SOC and is described Equation 1 while θ_{ik}^{mis} is the true mean of *k*th missing broad SOC in the *i*th major SOC.

Equation 1

$$Y_{ij}^{obs} \sim N(\theta_{ij}^{obs}, \frac{(s_{ij}^{obs})^2}{n_{ij}^{obs}})$$

The random variables θ_{ij}^{obs} can be thought of as independent samples from the major SOC with index , i , described by some fixed but unknown feature parameter θ_i and σ^2 where θ_i is the true mean of *i*th major SOC and σ^2 is the variation of broad SOCs within this major SOC. Similarly, the random variables θ_{ik}^{mis} can also be thought of as independent samples from the major SOC with index , i , described by θ_i and σ^2. In the normal model, we model the data as conditionally independent and identically distributed (i.i.d.) normal (θ_i, σ^2):

$$\theta_{ij}^{obs} \sim N(\theta_i, \sigma^2)$$
$$\theta_{ik}^{mis} \sim N(\theta_i, \sigma^2)$$

To represent the information about θ_i, we treat $\theta_i, i = 1, \ldots, I$ as independent samples from the population mean. Assume the true population mean level is μ and the variation among all major SOCs is τ^2. Then the distribution of θ_i is:

$$\theta_i \sim N(\mu, \tau^2)$$

In sum, we have a hierarchical normal model that describes the heterogeneity of means across different broad SOCs and major SOCs. In this hierarchical model we assume that the within- and between-major SOC sampling models are both normal. We further assume that the sample mean of each broad SOC is distributed around the true mean of that broad SOC. The within-major SOC sampling variability σ^2 is assumed to be constant across major SOC groups and the between-major SOC sampling variability τ^2 is also assumed to be constant. The fixed but unknown parameters in this model are $\theta_{ij}^{obs}, i = 1, \ldots, I; j = 1, \ldots, n_i^{obs}, \theta_{ik}^{mis}, i = 1, \ldots, I; k = 1, \ldots, n_i^{mis}$, $\theta_i, i = 1, \ldots, I$ and μ, τ^2, σ^2 which will be estimated. For the parameters μ, τ^2, σ^2, we need to specify prior distributions on them. We chose to use the standard conjugate normal and inverse-gamma prior distributions for these parameters as shown in equation 2.

Equation 2

$$\tau^2 \sim Inv - gamma\left(\frac{\eta_0}{2}, \frac{\eta_0 \tau_0^2}{2}\right);\ \sigma^2 \sim Inv - gamma\left(\frac{\upsilon_0}{2}, \frac{\upsilon_0 \sigma_0^2}{2}\right); \mu \sim N(\mu_0, \gamma_0^2)$$

Implying the densities $p(\tau^2) = \frac{1}{\tau^{2(\frac{\eta_0}{2}+1)}} \exp(-\frac{\eta_0 \tau_0^2}{2\tau^2})$ and $p(\sigma^2) = \frac{1}{\sigma^{2(\frac{\upsilon_0}{2}+1)}} \exp(-\frac{\upsilon_0 \sigma_0^2}{2\sigma^2})$.

Since no prior information is available, we specify non-informative priors for all these parameters. A graphical representation of the model is presented in Figure 4-2.

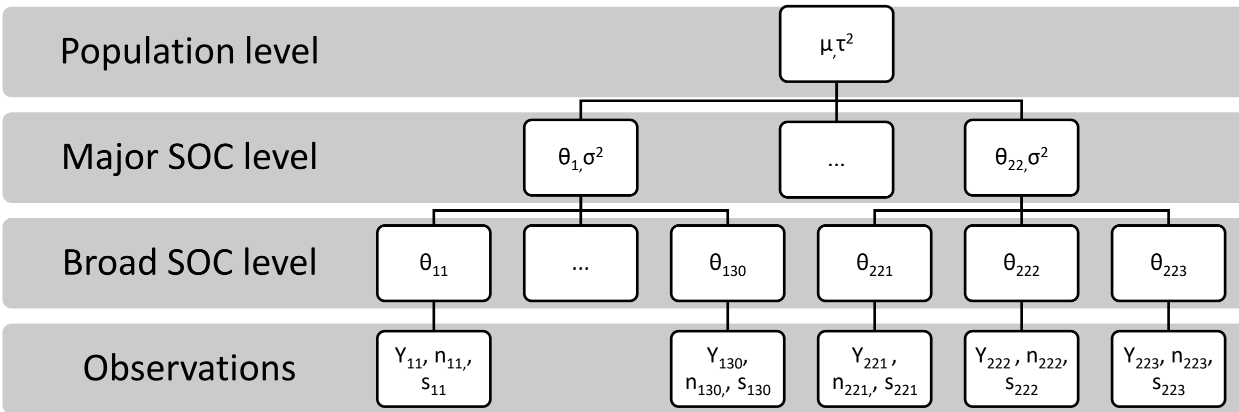


Figure 4-2 An illustration of the hierarchical structure used in this analysis. There are 22 major SOCs and various number of broad SOCs within each major SOC. For example, the first major SOC has 22 broad SOCs and the 22nd major SOC has 3 broad SOCs

The unknown quantities include the broad SOC means $\theta_{ij}^{obs}, i = 1, \dots, I; j = 1, \dots, n_i^{obs}, \theta_{ik}^{mis}, i = 1, \dots, I; k = 1, \dots, n_i^{mis}$, the major SOC means $\theta_i, i = 1, \dots, I$, the population mean μ, the within major SOC sampling variability σ^2 and the between major SOC sampling variability τ^2. Posterior inference for these parameters can be made by constructing a Gibbs sampler, which approximates the posterior distribution. After some calculation, we find that the conditional distribution of every mean parameter, including the broad SOC means $\theta_{ij}^{obs}, i = 1, \dots, I; j = 1, \dots, n_i^{obs}, \theta_{ik}^{mis}, i = 1, \dots, I; k = 1, \dots, n_i^{mis}$, the major SOC means $\theta_i, i = 1, \dots, I$, the population mean μ, is normal. The conditional distribution of SOC sampling variability σ^2 and the conditional distribution of the between major SOC sampling variability τ^2 are both inverse gamma.

Posterior approximation proceeds by iterative sampling of each unknown quantity from its full conditional distribution. We choose the number of iterations S to be 10000 and set the starting values for each of these parameters. Given a current state of the unknowns $\left\{\theta_{11}^{obs(s)}, \dots, \theta_{In_I}^{obs(s)}, \theta_{11}^{mis(s)}, \dots, \theta_{In_I}^{mis(s)}, \theta_i^{(s)}, \mu^{(s)}, \tau^{2(s)}, \sigma^{2(s)}\right\}$, a new state is generated as follows:

1. Posterior step: sample $\theta_i^{(s+1)}, i = 1, \dots, I$ from $\theta_i | \mu^{(s)}, \theta_{i1}^{obs(s)}, \dots, \theta_{in_i}^{obs(s)}, \theta_{i1}^{mis(s)}, \dots, \theta_{in_i}^{mis(s)}, \tau^{2(s)}, \sigma^{2(s)}$ based on its full conditional distribution
2. Posterior step: sample $\mu^{(s+1)}$ from $\mu | \theta_1^{(s+1)}, \dots, \theta_I^{(s+1)}, \tau^{2(s)}$
3. Posterior step: sample $\tau^{2(s+1)}$ from $\tau^2 | \theta_1^{(s+1)}, \dots, \theta_I^{(s+1)}, \mu^{(s+1)}$
4. Posterior step: sample $\sigma^{2(s+1)}$ from $\sigma^2 | \theta_{11}^{obs(s)}, \dots, \theta_{In_I}^{obs(s)}, \theta_{11}^{mis(s)}, \dots, \theta_{In_I}^{mis(s)}, \theta_1^{(s+1)}, \dots, \theta_I^{(s+1)}$
5. Posterior step: sample $\theta_{ij}^{obs(s+1)}, i = 1, \dots, I, j = 1, \dots, n_i^{obs}$ from $\theta_{ij}^{obs} | \theta_i^{(s+1)}, \sigma^{2(s+1)}$
6. Imputation step: sample $\theta_{ij}^{mis(s+1)}, i = 1, \dots, I, j = 1, \dots, n_i^{mis}$ from $\theta_{ij}^{mis} | \theta_i^{(s+1)}, \sigma^{2(s+1)}$

Repeat the above procedure for S times when convergence has already reached. After a thinning procedure and a burn-in period, the draws will be used for the posterior inference. This process is illustrated in figure 4-3. A detail description of this Bayesian parametric imputation procedure is presented in Appendix 1.

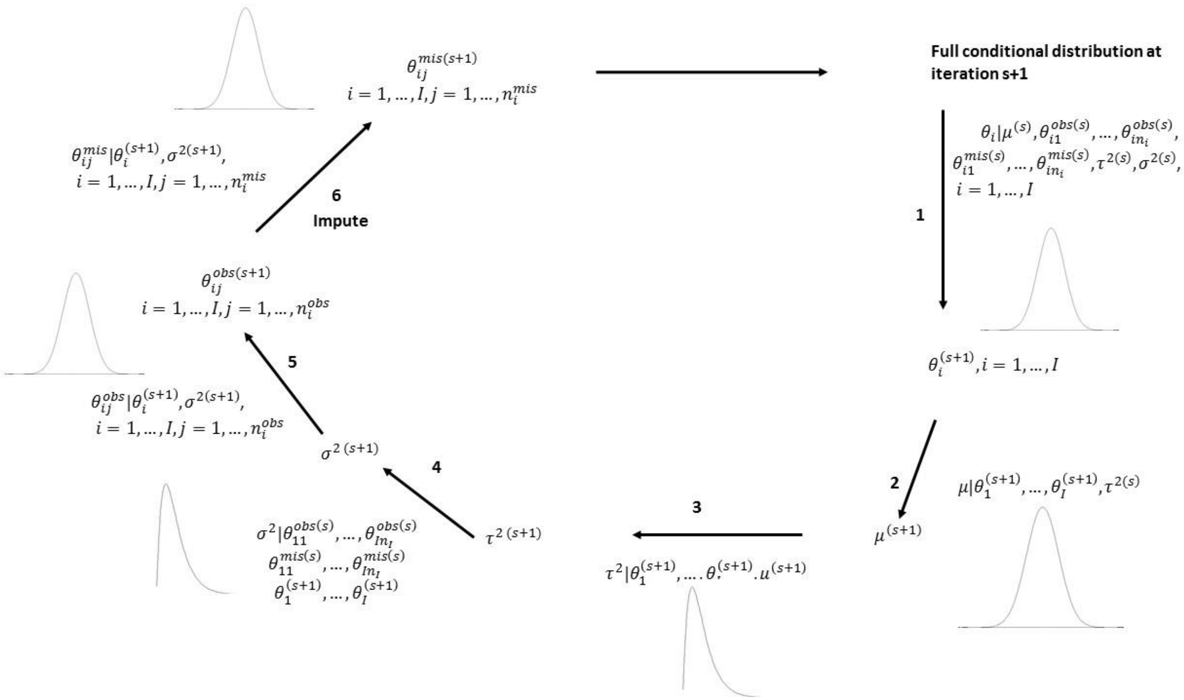


Figure 4-3 An illustration of the imputation process used to estimate exposures

Prior to imputation of the full JEM, the imputation model was evaluated by dividing the available data in to a training and validation set. The training dataset consisted of 189 broad SOCs that were randomly chosen from the available dataset of 239 broad SOCs provided the broad SOC contained more than one measurement, as imputation cannot be conducted with one measurement. The remaining 50 broad SOCs, including those with a single measurement, were assigned to the validation dataset. The posterior distribution of the mean and variances was calculated at the broad and major SOC level in the training dataset and compared to the observed data in the validation dataset. After the model evaluation the training and validation datasets were combined and all data were used for imputation of the final JEM.

Results

A summary of the estimates from the model validation is presented in Table 4-1, where the population mean (μ), is estimated to be 82.4 dBA, the within-major SOC variability (σ^2) is 20.0 and the between-major SOC variability (τ^2) is 13.3. The estimated mean noise exposure for each major SOC ranged from 78.4 (43-0000, "Office and Administrative Support Occupations") to 85.5 dBA (45-0000. "Farming, Fishing, and Forestry Occupations"). The 95% credible interval varied depending on the number of broad SOCs present within each major SOC (Table 4-2). Figure 4-4. displays a fairly strong agreement between the 189 estimated and observed broad SOC means in the training dataset. However, Figure 4-3b illustrates that the agreement between the observed and predicted SOC means in the validation dataset was not as strong as the training dataset as expected. Of the 50 broad SOCs in the validation dataset 11 observed sample means were outside the 95% credible interval and 39 fell inside the credible interval, however, 7 of those broad SOCs that fell outside contained only one measurement (Figure 4-5).

Parameter	**Posterior mean**	**Posterior standard deviation**	**95% Credible interval**
μ	82.3	0.90	(80.64, 84.19)
σ^2	20.0	2.51	(15.66, 25.48)
σ	4.4	0.28	(3.96, 5.05)
τ^2	13.3	5.28	(6.22, 26.50)
τ	3.5	0.68	(2.49, 5.15)

Table 4-1 Summary of posterior distribution of parameters from the model validation

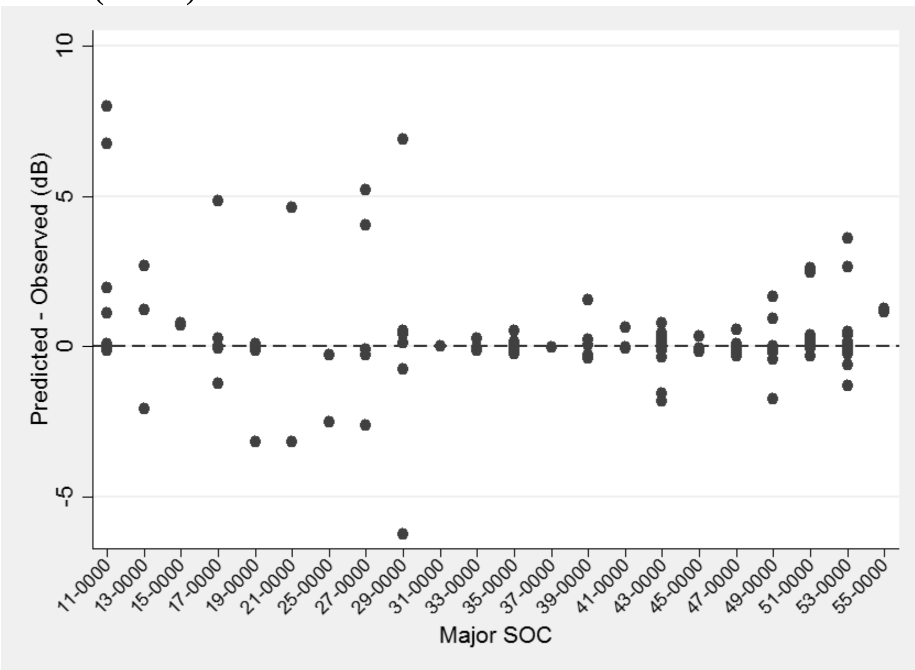
Major SOC	**Major SOC Title**	**Posterior mean**	**Posterior standard deviation**	**95% credible interval**	**Number of broad SOCs[1]**
11-0000	Management Occupations	81.8	1.77	(78.42, 85.28)	7
13-0000	Business and Financial Operations Occupations	82.7	2.38	(78.2, 87.6)	3
15-0000	Computer and Mathematical Occupations	80.9	2.72	(75.41, 86.1)	2
17-0000	Architecture and Engineering Occupations	80.7	1.63	(77.58, 84)	7
19-0000	Life, Physical, and Social Science Occupations	82.8	2.01	(78.88, 86.83)	4
21-0000	Community and Social Service Occupations	80.7	2.83	(74.73, 86.01)	2
25-0000	Education, Training, and Library Occupations	84.0	2.85	(78.53, 89.57)	2

[1] Number of broad SOCs in the training dataset

27-0000	Arts, Design, Entertainment, Sports, and Media Occupations	82.1	2.00	(78.22, 86.05)	5
29-0000	Healthcare Practitioners and Technical Occupations	79.9	1.82	(76.19, 83.26)	6
31-0000	Healthcare Support Occupations	82.3	2.91	(76.59, 87.97)	1
33-0000	Protective Service Occupations	81.2	1.82	(77.55, 84.74)	5
35-0000	Food Preparation and Serving Related Occupations	82.7	1.56	(79.65, 85.93)	8
37-0000	Building and Grounds Cleaning and Maintenance	85.0	2.53	(80.23, 89.84)	2
39-0000	Personal Care and Service Occupations	84.8	1.93	(80.91, 88.58)	5
41-0000	Sales and Related Occupations	82.3	2.07	(78.23, 86.59)	3
43-0000	Office and Administrative Support Occupations	78.4	1.15	(76.19, 80.61)	16
45-0000	Farming, Fishing, and Forestry Occupations	85.5	1.98	(81.65, 89.49)	4
47-0000	Construction and Extraction Occupations	83.5	0.85	(81.84, 85.12)	27
49-0000	Installation, Maintenance, and Repair Occupations	83.3	1.18	(80.96, 85.51)	14
51-0000	Production Occupations	85.2	0.68	(83.87, 86.59)	43
53-0000	Transportation and Material Moving Occupations	83.3	0.97	(81.45, 85.22)	21
55-0000	Military Specific Occupations	78.9	2.77	(73.2, 83.85)	2

Table 4-2 Posterior distribution of major SOC means from the model validation

a) Difference between predicted and observed broad SOC means in the training dataset (n=189).



b) Difference between predicted and observed broad SOC means in the validation dataset (n=50).

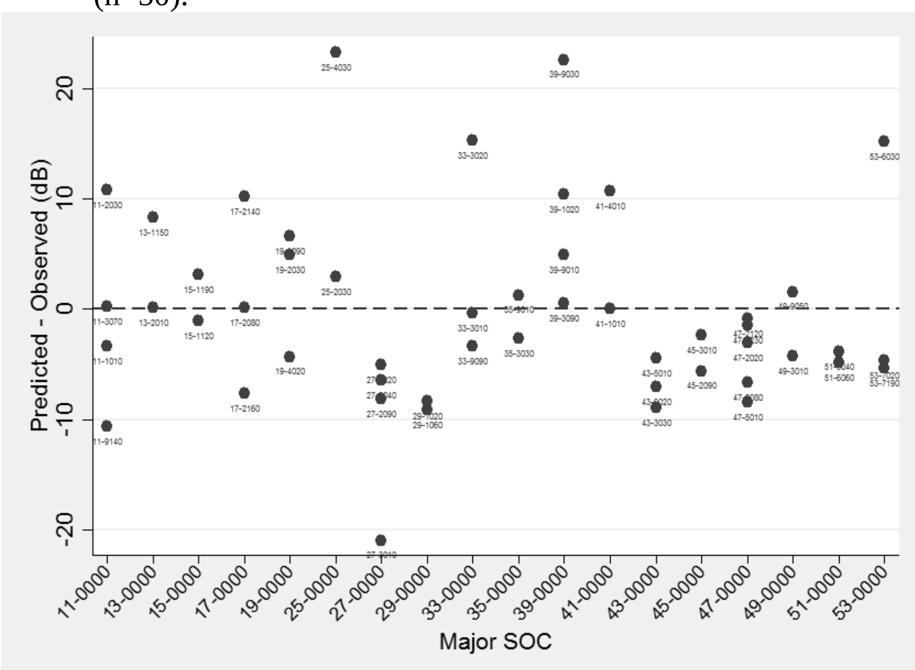


Figure 4-4 Difference between predicted and observed values for observed and predicted values

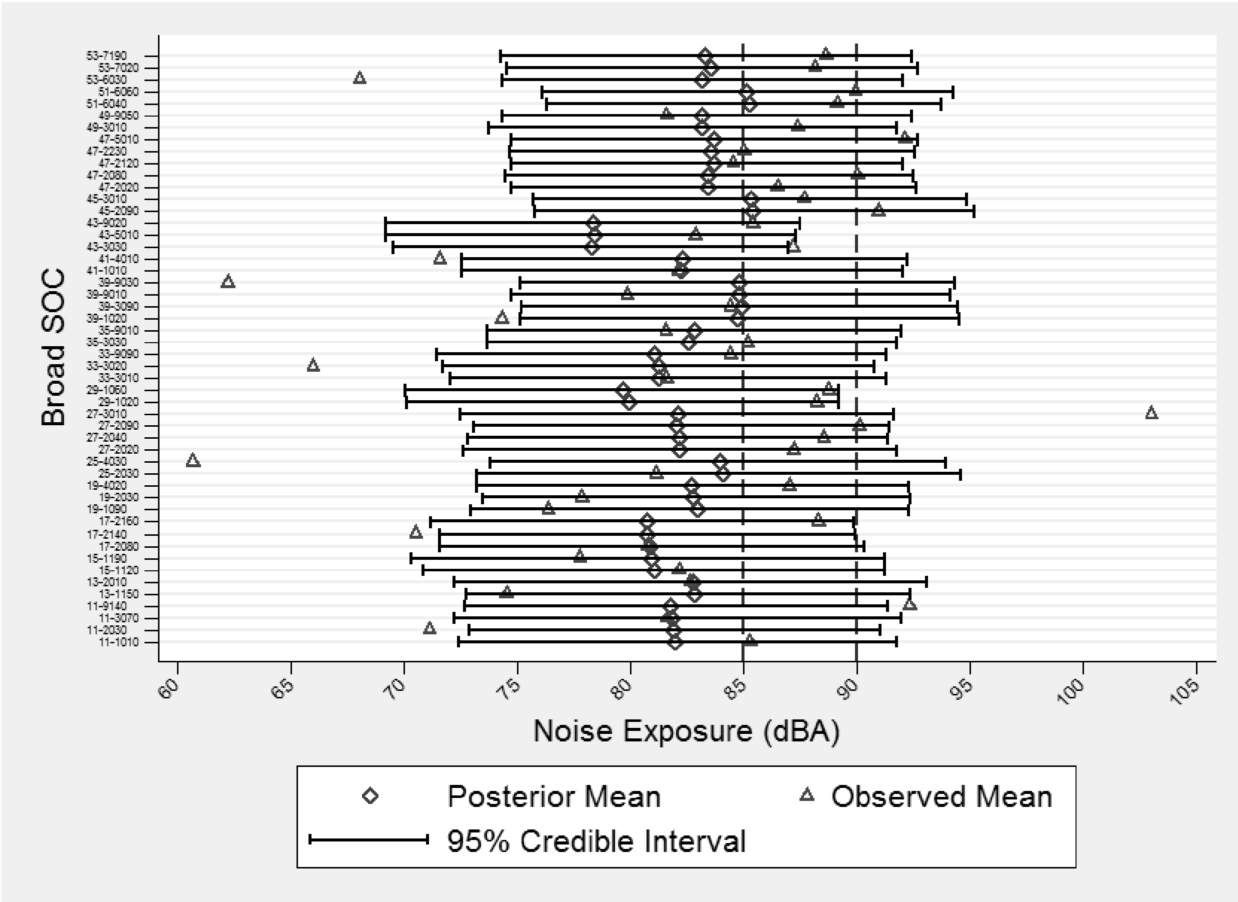


Figure 4-5 Posterior and observed broad SOCs means for the validation dataset (n=50)

Table 4-3 summarizes the population mean, and the within- and between-major SOC variability for the entire dataset (i.e. the combined validation and training datasets). The population mean was estimated to be 82.1 dBA and the within- and between-major SOC variability was estimated to be 22.1 and 13.8, respectively. As seen in table 4-4,The estimated mean noise exposure for each major SOC ranged from 78.6 (25-0000, "Education, Training, and Library Occupations") to 86.4 dBA (45-0000, "Farming, Fishing, and Forestry Occupations"). Similar to what we observed in the model validation results (Table 4-2), major SOCs that consisted of a larger number of broad SOCs had smaller 95% credible intervals.

Parameter	Posterior mean	Posterior standard deviation	95% Credible interval
μ	82.1	0.91	(80.30, 83.93)
σ^2	22.1	2.49	(17.73, 27.52)
σ	4.7	0.26	(4.21, 5.25)
τ^2	13.8	5.37	(6.56, 26.57)
τ	3.7	0.68	(2.56, 5.15)

Table 4-3 Summary of posterior distribution of parameters from the model imputation

The model predictions at the broad SOC level can be found in Appendix 2. The estimated population mean was 82.1 dBA while the estimated population standard deviation was 3.1 dBA. Of the 443 broad SOCs, 338 (76.3%) were found to have an estimated mean exposure >80 dBA, while 85 (19.2%) were found to have an estimated mean exposure greater than the current OSHA AL. Additionally, 10 broad SOCs were found to have an estimated mean exposure greater that the OSHA PEL. The distribution of estimated broad SOC means can be found in Figure 4-6, and indicates that the majority of broad SOCs have estimated mean noise exposure levels between 80 and 85 dBA.

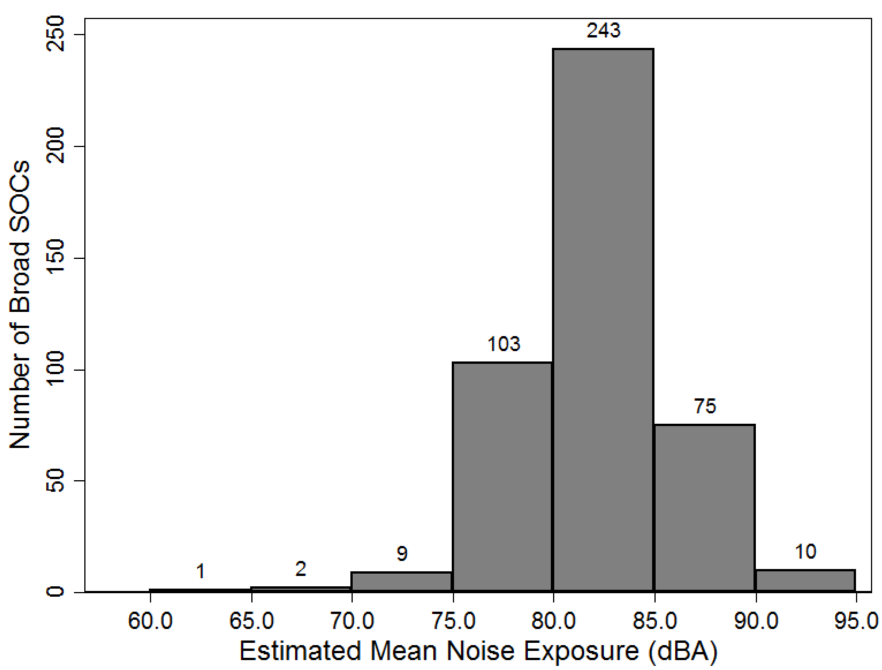


Figure 4-6 The distribution of estimated mean noise exposures (dBA) at the broad SOC

Major SOC	Major SOC Title	Posterior mean	Posterior standard deviation	95% credible interval	Number of broad SOCs[2]
11-0000	Management Occupations	82.0	1.63	(78.63, 85.13)	9
13-0000	Business and Financial Operations Occupations	81.4	2.03	(77.25, 85.12)	5
15-0000	Computer and Mathematical Occupations	80.4	2.27	(75.89, 84.77)	4
17-0000	Architecture and Engineering Occupations	81.3	1.54	(78.3, 84.4)	9
19-0000	Life, Physical, and Social Science Occupations	81.4	1.85	(77.74, 85.06	6
21-0000	Community and Social Service Occupations	80.6	2.99	(74.7, 86.29)	2
25-0000	Education, Training, and Library Occupations	78.6	2.23	(74.09, 82.94)	4
27-0000	Arts, Design, Entertainment, Sports, and Media Occupations	83.5	1.85	(79.95, 87.12)	7
29-0000	Healthcare Practitioners and Technical Occupations	81.5	1.70	(78.18, 84.85)	8
31-0000	Healthcare Support Occupations	82.1	2.94	76.41, 87.98)	1
33-0000	Protective Service Occupations	79.7	1.64	(76.47, 82.92)	7
35-0000	Food Preparation and Serving Related Occupations	82.8	1.42	(79.97, 85.63)	10
37-0000	Building and Grounds Cleaning and Maintenance	84.6	2.55	(79.7, 89.79)	2
39-0000	Personal Care and Service Occupations	84.6	1.83	(81.04, 88.19)	7
41-0000	Sales and Related Occupations	81.1	1.89	(77.39, 84.77)	5
43-0000	Office and Administrative Support Occupations	78.8	1.13	(76.59, 80.98)	18
45-0000	Farming, Fishing, and Forestry Occupations	86.4	1.75	(83.04, 89.81)	6
47-0000	Construction and Extraction Occupations	83.6	0.88	(81.88, 85.26)	29
49-0000	Installation, Maintenance, and Repair Occupations	83.3	1.16	(81.18, 85.65)	16
51-0000	Production Occupations	85.4	0.72	(84.02, 86.79)	45
53-0000	Transportation and Material Moving Occupations	83.7	1.00	(81.77, 85.69)	23
55-0000	Military Specific Occupations	78.8	2.78	(73.14, 84.12)	2

[2] Total number of broad SOCs in the training and validation datasets

Table 4-4 Posterior distribution of major SOC means from the model imputation

Discussion

In this study we used principled validation strategy to evaluate the performance of an imputation strategy to estimate noise exposures in a large JEM. The imputation strategy borrows information across broad SOCs by assuming a common hierarchical distribution with parameters that are shared. The imputed SOC means were assessed for imputation accuracy in a validation dataset consisting of randomly chosen subset of SOCs. The strong agreement between the 189 estimated and observed broad SOC means in the training dataset was because these observed broad SOCs were used to build the hierarchical model and thus their data were "known" to the model, which yielded statistically overly optimistic estimates. The broad SOCs in the validation dataset were not used in building the hierarchical model and were thus "unknown". The estimated SOC mean of a broad SOC in the training set was a weighted average of the observed SOC mean Y_{ij}^{obs} and the estimate of minor SOC mean θ_i that it was nested in, and the weights were proportional to the estimated σ^2 (variation within major SOC) and $\frac{\left(s_{ij}^{obs}\right)^2}{n_{ij}^{obs}}$ (variation in the observed SOC mean). As the variation within major SOCs was high in this dataset, and the variation in the observed SOC mean was very low for most broad SOCs, the estimated SOC mean would likely to be leaning towards the observed SOC mean. However the estimated mean of a broad SOC in the validation set was entirely based on the estimated mean of the major SOC that it was nested in; no additional information was available that could be used for this purpose. As a result, the agreement between the observed and predicted SOC means in the validation dataset were not as strongly associated as the training dataset.

Our estimates were developed from large datasets of measurements provided by the government, private industry, and the published literature. By taking advantage of the hierarchical structure of the SOC system we were able to use imputation to iteratively impute the missing values of the mean of the broad SOCs and to draw updated samples of the parameters based on both the means of the observed broad SOCs and the means of the missing broad SOCs. Due to the limited sample size within each minor SOC, we chose to ignore the minor SOC level in this hierarchical model. Instead we assumed that the broad SOCs within the same major SOC are more alike those broad SOCs in other major SOCs. This assumption has the potential to introduce error in the exposure estimates if the majority of broad SOCs within a major group were clustered under one minor group with the other minor groups only containing a few broad SOC measurements. However, any such error stems from the available data rather than the model used for this analysis. The imputation strategy is based on a parametric hierarchical model relying on normality and homogeneous variance within a broad SOC. These assumptions could be violated leading to erroneous imputation. The validation analysis on the 50 randomly chosen SOCs provide a realistic sense of accuracy when a new missing exposure is predicted for an SOC.

In the parametric Bayes imputation method that we used, we plugged in the posterior mean estimates of the unknown quantities as our single imputation results. However instead we could possibly create random draws from the posterior distributions of these quantities and then create multiple imputed datasets. The advantage of multiple imputation over the single imputation is that it takes into account the uncertainty in the imputation procedure.

Another potential source of error in our exposure estimates occurs because these data represents occupational noise exposures from 1970-2014. As reported by Middendorf in 2004 and Roberts et al. in 2016 occupational noise exposures have been decreasing overall in the general industry and mining sectors.[63,93] If a majority of measurements for a particular occupation were clustered in a short time span then it is possible that the measurements used by the model to develop exposure estimates may be biased.

The largest potential source of error in our estimates is likely the variability of exposure within each broad SOC. This is a common issue for any JEM that attempts to quantify exposures across several different industries. As identified by Rappaport et al. there is considerable variation in personal exposure for workers with similar job titles within the same workplace [89]. Grouping workers by job title is common practice in industrial hygiene because it is easy and straightforward to assign workers to an occupational group. However, as Anderson et al. have demonstrated, the standard occupational coding systems used in Canada were inadequate to accurately group workers in the pulp and paper industry.[96] We recognize that these shortcomings of the SOC system may result in misclassification of exposure. However, these issues are minimized by the large number of measurements and by use of the imputation method to estimate exposures from a distribution of possible exposures.[97]

The results of our analysis indicated that the majority of broad SOCs were estimated to be exposed to noise ≥ 80.0 and <85.0 dBA. While these broad SOCs are not estimated to exceed the OSHA action level, it is worth noting that the average estimated exposure and standard deviation for broad SOCs in this group were 82.3 and 3.6 dBA, respectively, with a 95% confidence interval between 72.3 and 89.4 dBA. This suggests that while the estimated mean exposure for these groups was below the action level there is considerable uncertainty in these exposures that must be considered when using these estimates to identify occupations that should be enrolled in hearing conservation programs (HCPs). This is in contrast to broad SOCs that are in the >=85.0, <90.0 dBA and > 90.0 dBA groups, which have an average estimated exposure of 87.1, 91.6 dBA and standard deviations of 1.2 and 0.8 dBA, respectively. For these two groups there is far greater confidence that noise exposures exceed the action level or PEL and that controls must be implemented to protect workers from excessive exposure.

Exposure estimates for individual broad SOCs can be found in Appendix 2. While these estimates cannot replace personal measurement data, they do provide a starting point for occupational health professionals to identify workers who may be overexposed to noise. Additionally, the provided measure of variability will help inform and guide the decisions of occupational health professionals regarding workers in job groups whose exposure may vary from day to day depending on the specific work tasks being conducted.

To our knowledge the exposure estimates from our model are based on the most comprehensive dataset of occupational noise exposure ever collected. The only other instance of a comprehensive JEM developed for occupational noise was reported by Sjöström et al. in 2013. The authors of that paper used a mixture of 569 quantitative noise measurements and qualitative measurements made by expert judgment to assign exposure groupings for 129 unique job families.[88] In contrast to what has been seen in the US, occupational noise exposures in Sweden saw only a slight decrease from 1970 to 2004 which, likely reflects the difference in the dates of promulgation and enforcement of occupational health laws in the US compared to Sweden [63,88]. It is not straightforward to directly compare the results from our JEM to the JEM constructed by Sjöström et al. because we only used quantitative measurements in our JEM. In addition, Sweden uses a more protective noise exposure standard than OSHA (85 dBA criterion level and 3 dB time-intensity exchange rate) while OSHA uses the less protective 90 dBA criterion level and 5 dB time-intensity exchange rate, making it impossible to directly compare the measurements.[15]

Despite the limitations associated with this JEM we believe it represents a useful tool for occupational health professionals and researchers. Our future plans include combining the exposure estimates from this model with information on the frequency of noise exposure from Department of Labor's Occupational Information Network (O*NET) system by using responses from survey question 4.C.2.b.1.a, which asks respondents to provide a response from 0-100% "How often does this job require working exposed to sounds and noise levels that are distracting or uncomfortable?".[98] This will build on previous work by Choi et al. that used the responses from O*NET's databases to create statistical models to predict NIHL.[99] Our exposure estimates can also be used with noise-induced hearing loss models published by the International Organization for Standards (ISO) to predict hearing threshold levels of participants in the National Health and Nutrition Examination Survey (NHANES) which contains both audiometric and employment history data.[100,101] Each of these steps will yield better noise exposures estimates that can, in turn, be used to guide efforts to control noise exposures and reduce occupational NIHL.

Chapter 5 -Evaluating the Risk of Noise-Induced Hearing Loss Using Different Noise Measurement Criteria

Abstract

This study examines whether the Occupational Safety and Health Administration's (OSHA) average noise level (L_{AVG}) or the National Institute of Occupational Safety and Health's (NIOSH) equivalent continuous average (L_{EQ}) noise measurement criteria better predicts hearing loss. A cohort of construction workers was followed for 10 years (2000 to 2010), during which time their noise exposures and hearing threshold levels (HTLs) were repeatedly assessed. Linear mixed models were constructed with HTLs as the outcome, either the OSHA (L_{AVG}) or NIOSH (L_{EQ}) measurement criteria as the measure of exposure, and controlling for, age, gender, duration of participation, and baseline HTLs (as both a covariate or an additional repeated measure). Model fit was compared between models for HTLs at 0.5, 1, 2, 3, 4, 6, and 8 kHz using the Akaike Information Criterion (AIC). The 10^{th}, 50^{th}, and 90^{th} percentiles of hearing outcomes predicted by these models were then compared to the hearing outcomes predicted using the ISO1999:2013 model. The mixed models using the L_{EQ} were found to have smaller AIC values than the corresponding L_{AVG} models. However, only the 0.5, 3, and 4 kHz models were found to have an AIC difference greater than 2. When comparing the distribution of predicted hearing outcomes between the mixed models and their corresponding ISO outcomes it was found that L_{EQ} generally produced the smallest difference in predicted hearing outcomes. Despite the small difference and high correlation between the L_{EQ} and L_{AVG} the L_{EQ} was consistently found to better predict hearing levels in this cohort.

Introduction

It is estimated that about 24 million workers are exposed to hazardous levels of occupational noise each year in the US alone.[6] Prolonged exposure to hazardous noise can lead to noise induced hearing loss (NIHL), which is estimated to affect 11.4% of the working population in the US.[78] NIHL can diminish a worker's ability to detect audible warnings and hinder communication with coworkers[102], and may also increase the risk of injury in the workplace.[38,43,103–106] Outside of the workplace those with NIHL can feel socially isolated and have a higher prevalence of depression and anxiety compared to those without hearing loss.[60]

Regulations and recommendations with regards to occupational noise exposure have changed since the first noise exposure limit was introduced in the 1950s.[107] Before the founding of the Occupational Health and Safety Administration (OSHA), the Department of Labor (DOL) used its authority under the Walsh-Healey Public Contracts Act to propose a Permissible Exposure Limit (PEL) for noise of 85 dBA with a time-intensity exchange rate (ER) – i.e., the amount of change in average noise level needed to double or halve the allowable exposure time – varying between 2 and 7 dB based on the intermittency of the noise exposure.[108] However, this standard was quickly replaced by a PEL of 90 dBA with a simplified 5 dB ER, which was adopted by OSHA when that agency was established in 1971 and which remains in effect today.[109–112] In 1972 the National Institute of Occupational Safety and Health (NIOSH) released its initial Criteria for a Recommended Standard for Occupational Exposure to Noise in which NIOSH "reluctantly concurred with the generally acceptable 90 dBA exposure level for an 8-hour day." However, NIOSH also recognized the need to for reducing the 8 hour exposure level to 85 dBA based on the evidence presented in the document.[113] In this document NIOSH did not take a position on the appropriate ER. In 1994 the American Conference of Governmental

Industrial Hygienists (ACGIH) revised its threshold limit value (TLV) for noise to be 85 dBA with a 3 dB ER.[114] NIOSH revisited the issue in 1998 when they released a revised Criterion for a Recommended Standard Occupational Exposure to Noise with a recommended exposure limit (REL) of 85 dBA and a 3 dB ER.[16] The difference between the 5 dB and 3 dB exchange rates has a major impact on the allowable exposure durations for high levels of intermittent noise. For truly non-varying noise the ER used makes no difference, but as noise becomes more variable, as is commonly the case in many industries such as construction, the difference between the two ERs becomes increasingly important.[115]

The divergence between the OSHA regulation and NIOSH recommendation for occupational noise exposure has been a point of contention in the industrial hygiene profession.[116–119] However, much of the debate has focused on the differing exchange rates rather than the differing exposure limits. The 3 dB ER is based on the equal energy hypothesis, which states that that an equal amount of sound energy will produce an equal amount of hearing damage regardless of the temporal distribution of the exposure over a work shift or longer period.[109] This was supported mainly by the research done by Eldred et al. in 1955 and was further buttressed by Burns and Robinson in 1970.[109] Since then several studies have provided further support to the equal energy hypothesis, and field studies using the 3 dB ER have found NIHL rates that are similar to those documented in ISO 1990:1999 (now ISO 1999:2013).[101,120–123]

Unlike the 3 dB ER, the 5 dB ER used by OSHA attempts to account for predictable, intermittent exposure to noise (e.g., noise exposures interrupted by regularly spaced quiet breaks) that may occur in the workplace. However, there is no formal definition in OSHA’s noise standard of what the distinction is between continuous and intermittent noise. The 5 dB ER was first suggested in a set of damage risk criteria curves published by the Committee on Hearing, Bioacoustics, and Biomechanics' (CHABA) Intersociety Committee in its 1967 guidelines for controlling noise exposure.[124] ACGIH also initially endorsed a 5 dB ER in 1969.[125] In the same year the Department of Labor adopted a regulation virtually identical to ACGIH's standard.[125]

Despite the fact that most countries have adopted the 3 dB ER for regulatory standards, and the much of the published literature supports using the 3 dB ER, some authors argue that there is insufficient evidence to support this presumably more protective ER.[15,126–128] The main argument put forth by those opposed to the 3 dB ER is that there are very few modern studies examining whether the 3 or 5 dB ER produces better exposure estimates for predicting NIHL, and some older studies found that using a 3 dB ER would lead to an overestimated risk of NIHL.[123]

Because it is widely accepted that hazardous noise exposure leads to NIHL, it is unethical to conduct experimental human exposure studies. Animal studies, primarily of chinchillas[129], have found that the same amount of noise exposure produces a similar amount of NIHL regardless if the noise exposure occurs with breaks or continuously, suggesting that the equal energy hypothesis, and thus the 3 dB ER, is acceptable.[130,131] However, there is still considerable uncertainty when extrapolating these results to humans due to inter-species differences in NIHL risk and the use of noise exposures that are not characteristic of exposures in the workplace.[132–134] Studies of highly-exposed worker populations are challenging due to the need for long-term access to, and cooperation from, the workers. In addition, OSHA's hearing conservation amendment in 1981 required employers to provide an effective hearing conservation program to all employees exposed >85 dBA as an 8-hour TWA.[111] This resulted in a large increase in the use of hearing protection devices (HPDs),[135] which substantially complicates the estimation of personal noise exposures and subsequent study of NIHL risk.

Annual audiometric evaluations are used to determine the degree of change in hearing over time, which may be the result of noise exposure during the interval between tests. According to both the OSHA noise standard, and recommended practice, workers should receive a baseline audiogram before employment or being assigned to an area with hazardous noise. The test measures pure-tone hearing threshold levels (HTLs) at various audiometric test frequencies (0.5, 1, 2, 3, 4, 6, and sometimes 8 kHz) after a quiet period of at least 14 hours.[136] The worker is then given a subsequent audiogram annually. Evaluation of within-worker changes in hearing thresholds between baseline and subsequent audiograms allows for surveillance and identification of NIHL. While large, longitudinal audiometric datasets are maintained by corporations and organizations in the US and globally, these datasets are often not available to researchers, and the quality of the audiometric measurements (and supporting noise measurement data) contained in the datasets can be highly variable due to variations in testing procedures and environments, as well as supporting information collected at the time of the test.[137,138]

To overcome these difficulties, we have re-analyzed exposure and audiometric data from a research cohort of construction apprentices that were first described in Seixas et al. in 2004[139], and subsequently in 2012.[65] This inception cohort was chosen due to reported infrequent use of hearing protection and the availability of high-quality baseline and annual audiometric test data accompanied by a robust set of longitudinal noise measurements.[65,140] Using linear mixed models, we estimated the amount of NIHL experienced by these workers when using the 3 dB ER as well as the 5 dB ER to estimate noise exposure. We then compared the models to see which best fit the observed changes in audiometric hearing thresholds. Predictions from both models were then compared to the International Standard Organization's ISO model[101] for estimating NIHL.

Methods

The exposure and audiometric data for this analysis comes from a 10-year longitudinal study of commercial construction apprentices from eight different trades described previously by Seixas et al. in 2012.[65,141] The study was divided into two different phases. In phase 1 (2000-2005), construction apprentices were recruited during their first year of apprenticeship training, and were given baseline questionnaires and audiometric tests at 0.25, 0.5, 1, 2, 3, 4, 6, and 8 kHz using a Tremetrics RA 300 audiometer with TDH-39 headphones in a test van meeting OSHA's requirements for background noise.[141] Subjects were then given follow-up tests approximately every year for 4 years. Graduate students assumed to have non-harmful (i.e., <70 dBA) occupational exposures were recruited as control subjects.[121] Subjects who had completed at least two tests were re-recruited for additional yearly audiometric tests for another 4 years during phase 2 (2006-2010).[65] Audiograms were obtained at 0.5, 1, 2, 3, 4, 6, and 8 kHz using a Grason-Standler GSI-61 audiometer with ER-3A insert earphones (Eden Prairie, MN) in a test booth meeting the American National Standard Institute's (ANSI) criteria for an audiometric test environment.[65] To account for the two different phases a dummy variable was included in all statistical models to control for the phase of the study.

Exposure to noise was assessed using a task-based approach as described by Neitzel et al. in 2011.[140] The task-based noise levels were calculated from 1,310 full-shift noise measurements (with noise levels data logged at 1-min intervals and simultaneous recording of task involvement and timing by subjects) collected between 1997 and 2008 on commercial construction sites.[65] Information on task duration from the questionnaires were combined with task-specific noise levels and normalized to a 2000 hour working year to account for the large variability in the number of hours worked across subjects.[65] Exposure metrics were calculated for each subject within the interval between audiometric tests, and also cumulated over the subject's full duration in the study. Equation 1 from Seixas et al. 2012 calculates the L_{EQ} – the equivalent-continuous sound level using a 3 dB ER – where L_t is the mean L_{AVG} level for task *t* which was done for *H* hours as reported by individual *i* in the subject-interval *j* lasting *Y* years, and L_{NC} denotes non-construction hours in noisy jobs that were assigned a level of 85 dBA.

Equation 1

$$L_{EQijTB2000} = 10\log10[\frac{1}{2000 \times Y_{ij}}((\sum_{t=1}^{T} H_{ijt}10^{L_t/10}) + (H_{NCij}\times 10^{L_{NC}/10}))]$$

We used equation 2 in the current study to calculate the task-based L_{AVG}, which is the average sound level using a 5 dB ER, normalized to a 2000 hour working year.

Equation 2

$$L_{AVGijTB2000} = 16.61\log10[\frac{1}{2000 \times Y_{ij}}((\sum_{t=1}^{T} H_{ijt}10^{L_t/16.61}) + (H_{NCij}\times 10^{L_{NC}/16.61}))]$$

Controls were assigned an exposure of 70 dBA because noise exposure at this level will not cause any measurable hearing loss.[121] Pearson's correlation was calculated to measure the correlation between the L_{EQ} and L_{AVG} for each subject over each study interval and cumulatively for the study duration. The ratio of the L_{MAX} and L_{EQ} was calculated, using energy averaging to account for the fact that decibels are log-scale measurements to determine the peakiness of the exposure.

Linear mixed models were developed to predict HTLs in each ear over time at 0.5, 1, 2, 3, 4, 6 and 8 kHz; these are the audiometric test frequencies recommended as part of a comprehensive hearing loss prevention program.[16] Noise exposure metrics were transformed by subtracting 70, thus giving an 'unexposed' level of 0 dBA. Models were run using either the L_{AVG} or L_{EQ} exposure metric. The models were run using the combined data from phase 1 and 2 so that our results could be compared to those of Seixas et al. 2012.[65] The models were adjusted for the baseline covariates, age (<30 years ≥30 years) and gender. The models included random intercepts for subjects (b_{0i}), dominant ears nested within subjects ($b_{oi\cdot l}$), and a random slope for years since baseline at the subject level ($b_{1i\cdot l}$). An additional set of models was developed using the exposure metrics described previously, but which included the baseline hearing thresholds as an additional covariate. This was done to compare the model results to what was found by Seixas et al. 2012.[65]

The general equations for the linear mixed models are presented in equation 3 where i indexes the subject $i_1,...,i_{316}$, l the ear (dominant or non-dominant hand side) $l_1,\ldots,l_{617}$, and t indexes visit time since baseline $t_1,\ldots,t_9$.[65] The term T_{it} indexes the number of years for a subject since baseline at time t, X_{it} is the subject's cumulative noise exposure at time t, and $Z_{it\cdot l}$ represents the other fixed effect covariates for ear l nested within subject i at time t. By including the number of years since baseline and the cumulative noise exposure it was possible for the model to account for the effect of ageing in addition to noise exposure on HTLs.

Equation 3

$$Y_{it\cdot l} = \beta_0 + (b_{0i} + b_{0i\cdot l}) + (\beta_1 + b_{1i\cdot l})T_{it} + \beta_2 X_{it} + \beta_3 T_{it} + \gamma Z_{it\cdot l} + \varepsilon_{it\cdot l}$$

All models were run in STATA 14 (College Station, TX) using restricted maximum likelihood (REML) estimates and an unstructured covariance. This was done to minimize the bias in the variance component while providing the best model fit, and to be consistent with the previous analysis by Seixas et al.[65,142,143] The fit of the four L_{EQ} and L_{AVG} models (L_{EQ}

controlling for baseline vs. baseline as an additional repeated measure) and L_{AVG} controlling for baseline vs. baseline as an additional repeated measure) was compared by using the Akaike Information Criterion (AIC), a goodness of fit statistic that penalizes complex models.[144] Models with lower AIC values were deemed to better fit the data. The difference in AIC scores between the L_{EQ} and L_{AVG} models was calculated. A difference of 0-2 indicates that there is substantial evidence that both models fit the data, a difference of 4-7 indicates that one model fits the data considerably better, and a difference >10 indicates that one model does not fit the data.[145]

The 10th, 50th, and 90th percentiles of hearing outcomes from the four models were compared to the 10th, 50th, and 90th percentiles estimated levels of hearing loss associated with age and noise (NTLAN) predicted using the L_{EQ} and L_{AVG} exposure metrics in the model proposed in ISO1999:2013.[101] Briefly, this was done by first calculating the median level of predicted noise-induced permanent threshold shift (NIPTS) at the 0.5, 1, 2, 3, 4, and 6 kHz hearing frequency for each worker using equation 4 (from ISO1999:2013).[101] For both the L_{EQ} and L_{AVG} where N_{50} is the predicted median NIPTS, μ and v represent frequency dependent correction factors, t represents the length of exposure, t_0 represents 1 year, $L_{EX,8h}$ represents noise exposure for an 8 hour working day (either L_{EQ} or L_{AVG}), and L_0 represents the frequency dependent sound level at which effect on hearing is negligible.[101] For participants that had an exposure duration less than 10 years, N was extrapolated using equation 5 where $N_{50,\, t<10}$ represents the median NIPTS for exposures less than 10 years, t represents the exposure time (in years), and $N_{50,\, t=10}$ represents the estimated NIPTS at 10 years of exposure. Assuming a Gaussian (normal) distribution, the ISO model provides multiplier values that can be used with adjustment factors to calculate the 10th and 90th percentiles of the NIPTS distribution.

Equation 4

$$N_{50} = \left[\mu + v \times log\left({}^{t}/_{t_0}\right)\right] \times (L_{EX,8h} - L_0)^2$$

Equation 5

$$N_{50,t<10} = \frac{log(t+1)}{log(11)} \times N_{50,t=10}$$

HTLs as a function of age were calculated for the same audiometric frequencies using equation 6 where $H_{md,\,y}$ is the median hearing threshold due to age, *a* is the gender and frequency adjustment factor, *y* is the person's age, and $H_{md;18}$ is the median hearing threshold of an ontologically normal person that is 18 years old. Because the equation centers the age at 18 the $H_{md;18}$ term is taken as 0.   Different percentiles can be calculated for each frequency using the provided multiplier and adjustment factors. The HTL associated with age and noise was calculated at the 10th, 50th, and 90th percentiles using Equation 7 where H' is the hearing threshold associated with age and noise exposure, H is the hearing threshold associated with age, and N is the permanent threshold shift caused by noise exposure for the respective frequency and percentile.

Equation 6

$$H_{md,y} = a(y-18)^2 + H_{md;18}$$

Equation 7

$$H' = H + N - \frac{H \times N}{120}$$

Results

Figure 5-1 presents scatter plots of the L_{EQ} and L_{AVG} for each worker at each interval (Figure 5-1a) at which their noise exposure was estimated, as well as for their cumulative exposures (Figure 5-1b). The L_{EQ} measurements were on average 3-4 dB higher than their associated L_{AVG} measurements. For both interval-specific and cumulative exposures, the L_{EQ} and

L_{AVG} measurements were highly and significantly correlated (r = 0.968 and r = 0.974, respectively). The number of subjects available at each follow up is displayed in Table 5-1.

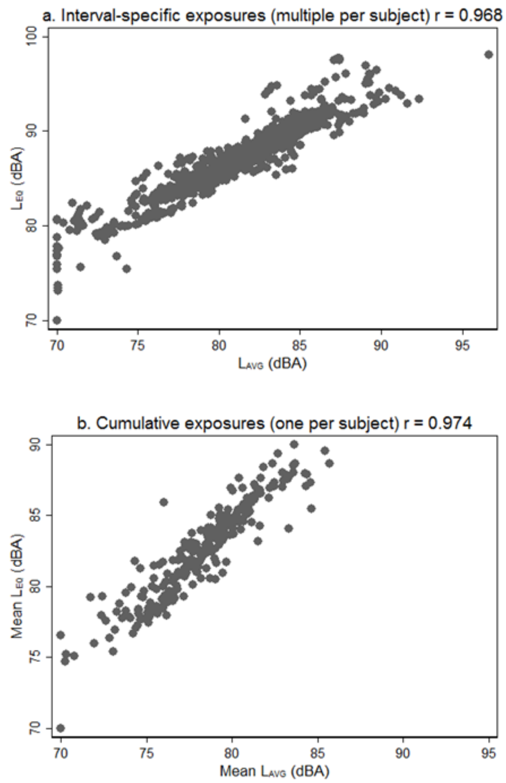


Figure 5-1 Scatter plot and correlation for a) interval-specific exposures and b) cumulative exposures

Time Point	Number of Subjects
1	316
2	308
3	308
4	259
5	203
6	132
7	110
8	86
9	41

Table 5-1 Number of subjects at each follow up.

Table 5-2 compares the AIC values for both the L_{EQ} and L_{AVG} models with and without the baseline HTL covariate at the 0.5, 1, 2, 3, 4, 6, and 8 kHz audiometric test frequencies. When the baseline HTLs were included the L_{EQ} models fit the data better than L_{AVG} models at each test frequency. However, only the 0.5, 3, and 4 kHz test frequencies were found to have an AIC difference >2 and only the 4-kHz frequency had a difference >4. When the baseline HTLs were not included as a covariate and instead treated as additional repeated measurements the L_{EQ} models better fit the data at all the test frequencies except for 2 kHz. In addition, the difference between the L_{EQ} and L_{AVG} models AIC decreased at all the test frequencies except for the 3 and 4 kHz frequencies, where the differences increased by about 2-3.

Audiometric Frequency (kHz)	**Models with baseline HTLs**			**Models without baseline HTLs**		
	L_{EQ}	**L_{AVG}**	**Difference (L_{EQ}-L_{AVG})**	**L_{EQ}**	**L_{AVG}**	**Difference (L_{EQ}-L_{AVG})**
0.5	16858.24	16860.76	-2.52	20010.75	20013.18	-2.43
1	16410.74	16412.56	-1.82	19459.59	19461.00	-1.41
2	17098.14	17098.55	-0.41	20226.13	20226.05	0.08
3	17468.53	17471.47	-2.94	20872.27	20877.10	-4.83
4	18538.37	18542.41	-4.04	22383.88	22389.32	-5.44
6	19394.87	19395.82	-0.95	23475.21	23475.85	-0.64
8	19928.21	19928.87	-0.66	23756.35	23756.39	-0.04

Table 5-2 Comparison of AIC values for the L_{EQ} and L_{AVG} models at 0.5, 1, 2, 3, 4, 6, and 8, kHz audiometric frequencies.

The fixed and random effects from the L_{EQ} and L_{AVG} models with the baseline HTLs for the 4-kHz test frequency are presented in Table 5-3. The coefficients associated with each covariate were generally similar between the L_{EQ} and L_{AVG} 4 kHz models. Those workers with higher baseline hearing levels were found to suffer worse hearing loss due to noise during the study than those in the baseline group in both models. Cumulative noise exposure had a small, but significant effect on hearing levels. This trend was consistent at these three frequencies that had an AIC difference >2, except at the 0.5 kHz frequency where cumulative exposure was found to be a significant predictor of hearing loss in the L_{EQ} model, but not in the L_{AVG} model.

	4 kHz L_{EQ}			4 kHz L_{AVG}		
Fixed Effects	**Coefficient**	**SE**	**P-value**	**Coefficient**	**SE**	**P-value**
Intercept	2.05	0.97	0.034	2.01	0.97	0.038
Phase 2	2.22	0.55	<0.001	2.28	0.55	<0.001
Age (>30)	3.03	0.9	0.001	3.02	0.9	0.001
Gender (male)	2.05	1.05	0.05	2.09	1.05	0.045
HTL at baseline (ref <10)						
10-20	7.49	0.79	<0.001	7.49	0.79	<0.001
>20	30.22	1.09	<0.001	30.22	1.09	<0.001
Years since BL	0.25	0.14	0.86	0.15	0.12	0.2
Noise exposure x years	0.02	0.01	0.003	0.02	0.01	0.034
Random Effects	**Estimate**	**SE**		**Estimate**	**SE**	
Subject: random intercept SD	4.78	0.48		4.78	0.48	
Subject: random slope SD	0.74	0.05		0.73	0.05	
Subject intercept-slope corr.	0.02	0.11		0.04	0.11	
Ear: random intercept SD	6.46	0.30		6.46	0.30	
Residual SD	4.20	0.70		4.20	0.070	

Table 5-3 Fixed and random effects for the L_{EQ} and L_{AVG} models with the baseline HTLs covariate for the 4-kHz hearing frequency

Table 5-4 presents the fixed and random effects for the L_{EQ} and L_{AVG} models with the additional repeated measurements. The coefficients for each covariate were very similar except for the number of year since baseline which was found to not be associated with changes in the HTLs in the L_{EQ} nor the L_{AVG} models.

	4 kHz L_{EQ}			4 kHz L_{AVG}		
Fixed Effects	**Coefficient**	**SE**	**P-value**	**Coefficient**	**SE**	**P-value**
Intercept	3.21	1.70	0.06	3.23	1.70	0.058
Phase 2	2.42	0.51	<0.001	2.49	0.51	<0.001
Age (>30)	7.55	1.57	<0.001	7.50	1.57	<0.001
Gender (male)	7.41	1.82	<0.001	7.39	1.82	<0.001
Years since BL	-0.06	0.14	0.680	0.11	0.12	0.367
Noise exposure x years	0.02	0.01	0.002	0.02	0.01	0.049

Random Effects	Estimate	SE	Estimate	SE
Subject: random intercept SD	10.89	0.57	10.89	0.57
Subject: random slope SD	0.82	0.06	0.82	0.06
Subject intercept-slope corr.	0.08	0.09	0.10	0.09
Ear: random intercept SD	7.67	0.33	7.67	0.33
Residual SD	3.97	0.05	3.98	0.05

Table 5-4 Fixed and random effects for the L_{EQ} and L_{AVG} models without baseline HTLs covariate for the 4-kHz hearing frequency

Table 5-5 compares the 10th, 50th, and 90th percentiles of hearing loss at the 0.5, 1, 2, 3, 4, and 6 kHz audiometric frequencies from the ISO hearing loss model using both the L_{AVG} and L_{EQ} exposure metric to the 10th, 50th, and 90th percentiles of hearing loss at the same frequencies predicted by our mixed models with the baseline HTLs. The difference between the ISO prediction and our models was similar for both the L_{EQ} and L_{AVG} exposure metrics. However, as seen in figure 5-2, 14 out of the 18 comparisons (77.7%) the mixed model using the L_{EQ} exposure metric more closely matched the estimated hearing loss that was calculated by the ISO model, suggesting that the L_{EQ} performs slightly better than the L_{AVG} in predicting hearing loss in this cohort.

Frequency (kHz)	LEQ Model	LEQ ISO	LEQ Difference	LAVG Model	LAVG ISO	LAVG Difference	Smallest Difference
10^{th} Percentile							
0.5	1.86	-5.76	7.62	1.87	-5.76	7.63	L_{EQ}
1	0.91	-5.61	6.52	0.91	-5.69	6.60	L_{EQ}
2	1.26	-6.34	7.60	1.26	-6.12	7.38	L_{AVG}
3	0.74	-6.53	7.27	0.72	-6.6	7.32	L_{EQ}
4	1.43	-5.88	7.31	1.42	-6.76	8.18	L_{EQ}
6	4.75	-8.56	13.31	4.76	-8.39	13.15	L_{AVG}
50th Percentile							
0.5	6.28	0.85	5.43	6.28	0.85	5.43	Same
1	5.62	1.69	3.93	5.62	0.97	4.65	L_{EQ}
2	6.69	2.18	4.51	6.68	1.66	5.02	L_{EQ}
3	7.37	4.83	2.54	7.38	2.66	4.72	L_{EQ}
4	8.44	6.66	1.78	8.41	3.64	4.77	L_{EQ}
6	12.82	5.99	6.83	12.84	4.12	8.72	L_{EQ}
90th Percentile							
0.5	13.53	9.19	4.34	13.51	9.17	4.34	Same
1	14.23	9.47	4.76	14.24	9.37	4.87	L_{EQ}
2	18.44	13.21	5.23	18.45	11.65	6.80	L_{EQ}
3	23.42	13.99	9.43	23.43	12.57	10.86	L_{EQ}
4	34.60	15.70	18.90	34.64	13.74	20.9	L_{EQ}
6	35.78	16.42	19.36	35.79	14.59	21.2	L_{EQ}

Table 5-5 Comparison of estimated hearing loss using the L_{EQ} and L_{AVG} exposure metrics in the ISO hearing loss and mixed models with baseline HTLs covariate

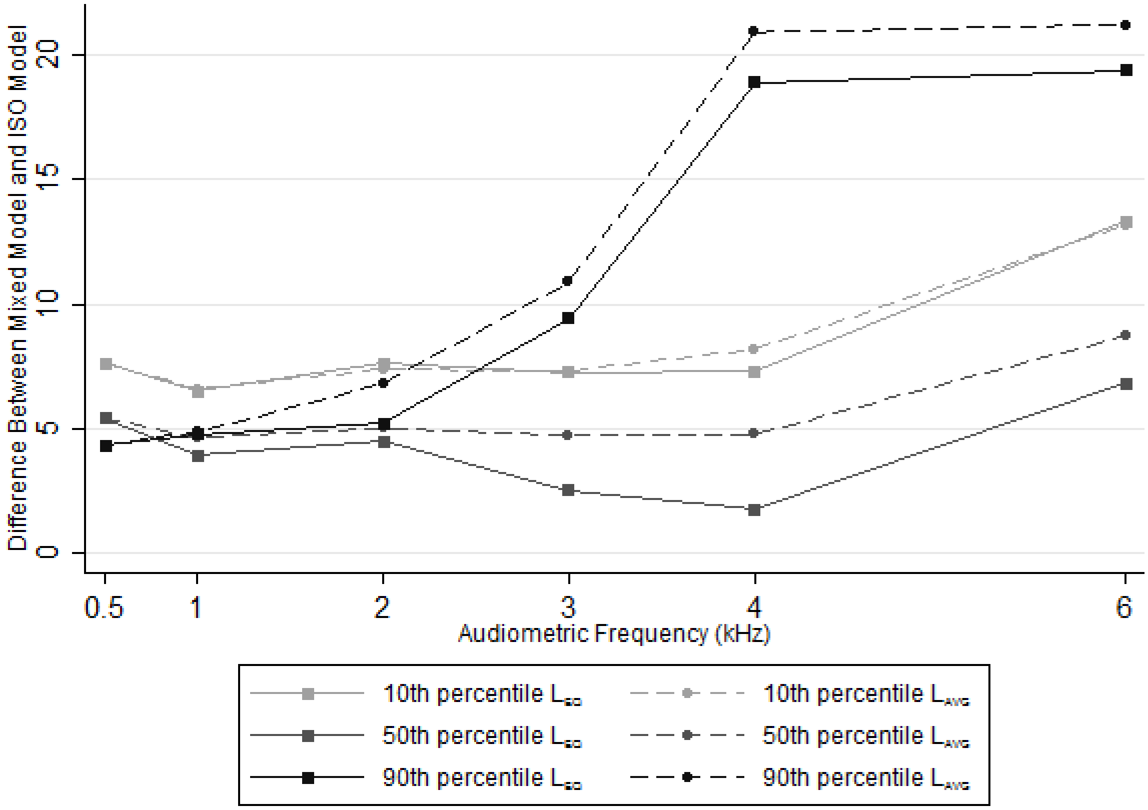


Figure 5-2 Difference between model (with baseline HTL covariate) and ISO predictions of hearing loss at the 10th, 50th, and 90th percentiles for the L_{EQ} and L_{AVG} metrics.

Table 5-6 presents the differences between the 10^{th}, 50^{th}, and 90^{th} percentiles of hearing loss at the same frequencies between the mixed models without the additional repeated measurements and the ISO hearing loss model using both the L_{EQ} and L_{AVG} exposure metrics. Figure 5-3 shows that for 13 out of 18 comparisons (72.2%) the L_{EQ} exposure metrics more closely matched the estimate hearing loss that was calculated by the ISO model. The mixed models using the L_{EQ} with the additional measurements were found to produce a better agreement with the ISO model than the mixed models with the baseline HTLs except for the 50^{th} percentile of the 6-kHz test frequency and the 90^{th} percentile 1 and 6 kHz test frequencies. Similarly, the mixed models using the L_{AVG} without the additional measurements were found to produce a better agreement with the ISO model than the mixed models including the baseline

HTLs expect for the 50th percentile of the 6 kHz test frequencies and the 90th percentiles at the 2 and 6 kHz test frequencies.

	L_{EQ}			L_{AVG}			
Frequency (kHz)	**Model**	**ISO**	**Difference**	**Model**	**ISO**	**Difference**	**Smallest Difference**
10th Percentile							
0.5	1.62	-5.76	7.38	1.62	-5.76	7.38	Same
1	0.63	-5.61	6.24	0.64	-5.69	6.33	L_{EQ}
2	0.93	-6.34	7.27	0.91	-6.12	7.03	L_{AVG}
3	0.47	-6.53	7.00	0.47	-6.6	7.07	L_{EQ}
4	1.19	-5.88	7.07	1.19	-6.76	7.95	L_{EQ}
6	4.67	-8.56	13.23	4.68	-8.39	13.07	L_{AVG}
50th Percentile							
0.5	6.11	0.85	5.26	6.12	0.85	5.27	L_{EQ}
1	5.39	1.69	3.70	5.4	0.97	4.43	L_{EQ}
2	6.5	2.18	4.32	6.47	1.66	4.81	L_{EQ}
3	7.25	4.83	2.42	7.26	2.66	4.60	L_{EQ}
4	8.25	6.66	1.59	8.23	3.64	4.59	L_{EQ}
6	13.33	5.99	7.34	13.34	4.12	9.22	L_{EQ}
90th Percentile							
0.5	13.39	9.19	4.20	13.37	9.17	4.20	Same
1	17.36	9.47	7.89	14.01	9.37	4.64	L_{AVG}
2	18.26	13.21	5.05	24.06	11.65	12.41	L_{EQ}
3	22.45	13.99	8.46	22.45	12.57	9.88	L_{EQ}
4	33.34	15.70	17.64	33.35	13.74	19.61	L_{EQ}
6	36.12	16.42	19.70	36.11	14.59	21.52	L_{EQ}

Table 5-6 Comparison of estimated hearing loss using the L_{EQ} and L_{AVG} exposure metrics in the ISO hearing loss and mixed models without the baseline HTLs covariate

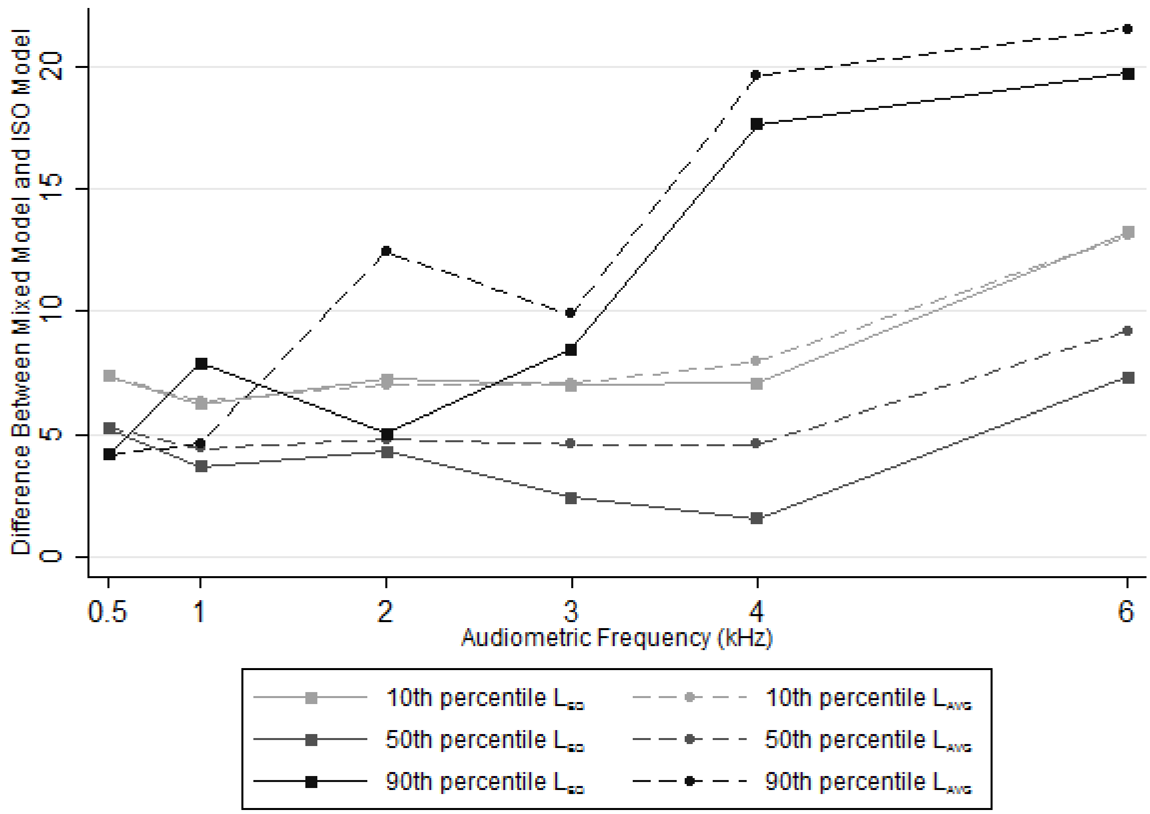


Figure 5-3 Difference between model (without baseline HTL covariate) and ISO predictions of hearing loss at the 10th, 50th, and 90th percentiles for the L_{EQ} and L_{AVG} metrics

Discussion

The debate on whether the L_{EQ} or L_{AVG} exposure metric is more predictive of NIHL risk is a controversial subject, and no single study will be able to conclusively settle this debate. However, this study suggests that the L_{EQ} is the more appropriate metric for predicting NIHL and provides a better foundation for developing exposure response relationships and providing guidance for the development of regulations and standards. One of the main strengths of our study is that it used a cohort of noise-exposed workers that were followed for approximately 10 years. This represents an exposure duration sufficient for NIHL to occur; in fact, the majority of loss expected over the course of a working lifetime in noise is predicted to occur within the first ten years of exposure.[101]

The first set of mixed models used in this analysis did not include a covariate for baseline HTLs. Instead, the baseline HTLs were considered as additional measurements in the model. This was done because audiometric tests have inherent variability and measurement error, as demonstrated by the statistically significant effect of the study phase on HTLs due to changes in equipment and operators.[146] In addition, the causal relationship between noise exposure and hearing loss, results in the inclusion of baseline HTLs in the model biasing the results towards the mean.[147] The additional repeated measurements in the models without the baseline adjustment still allow for us to account for an individual subject's change in HTLs over time without biasing the relationship between the exposure and hearing outcomes. Because of this we believe the models with the additional measurements are more appropriate than the models that control for baseline HTLs; however, we presented those models here to allow for comparison with the findings of Seixas et al. 2012.[65]

The second set of mixed models used in this analysis allowed us to control several covariates including age, hearing levels at baseline, and the number of years exposed to noise during the study, all of which can impact HTLs. When comparing the mixed model using the L_{EQ} to the mixed model using the L_{AVG} we found that the L_{EQ} model produced a lower AIC compared to the L_{AVG} model in at all test frequencies, indicating the L_{EQ} model had a better fit. However, the difference between the two models was generally small, and only three of seven test frequencies were found to have an AIC difference >2, i.e., a difference indicative of meaningfully different performance between the L_{AVG} and L_{EQ} models. It is worth noting that the 3 and 4 kHz test frequencies (along with 6 kHz) have been found to be most susceptible to noise-induced hearing loss.[24]

When the 10^{th}, 50^{th}, and 90^{th} percentiles of predicted hearing loss using the ISO model were compared to the same percentiles of predicted hearing loss from our mixed models with baseline HTLs, the L_{EQ} models showed better agreement. However, we found that in all cases our mixed models predicted greater NIHL than the ISO models. This is likely due to the fact that a subset of workers in this cohort had already experienced hearing loss prior to enrollment. These workers tended to have worse and more variable hearing outcomes compared to those who enrolled in the study with less or minimal hearing loss. The ISO model provides no way for preexisting hearing loss to be factored into the NIHL predictions based on age and known noise exposure.[101] When we compared the 10^{th}, 50^{th}, and 90^{th} percentile of predicted hearing loss from the mixed models with the additional measurements we again found that the L_{EQ} models showed better agreement with the ISO model than the L_{AVG} model, but overall the models without baseline HTLs had better agreement than the models with the baseline HTLs.

Recently there has been an increased interest in the impact of non-Gaussian noise – complex noise consisting of varying, intermittent, and interrupted exposures – on the risk and severity of NIHL. A recent contract report to NIOSH summarized the peer-reviewed literature and came to the conclusion that an exposure metric modified by a measure of kurtosis could provide a more accurate predictor of NIHL than simply the L_{EQ} or L_{AVG} alone.[148] To evaluate this possibility, we compared the AICs of our L_{EQ} and L_{AVG} mixed models with an added variable for peakiness, using metrics previously developed and evaluated by Seixas et al. on the same cohort of construction workers.[149] Following the inclusion of the peakiness metric the L_{EQ} model still demonstrated generally lower AIC values compared to its equivalent L_{AVG} model, but the difference between AICs was reduced to <2 for all models. The L_{EQ} was still a better fit in our model, but our finding that the inclusion of a measure of peakiness and resulting improvement in model fit suggests that a combination of the L_{EQ} and some sort of measure of kurtosis may further improve the model. Further research is needed to investigate the impact of including a measure of kurtosis on NIHL predictions.

Our study only examined the effects of noise exposures in construction workers, who are exposed to intermittent noise, so these results may not be generalizable to occupational groups that are exposed to truly continuous noise or who have regular, scheduled breaks from exposure. There is limited evidence to support the notion that most occupations have such breaks, consistent with the rationale behind the L_{AVG}.[115,150] The high correlation between the L_{EQ} and L_{AVG} exposure measurements made on construction workers resulted in similar levels of model fit and predicted hearing outcomes. This was further complicated by the fact that many of the construction workers evaluated here had pre-existing hearing loss. One set of mixed models controlled for this situation through the use of a categorical variable for baseline hearing level. The other set of mixed models instead used the baseline HTLs as additional measurements and excluded the fixed effect for baseline HTLs. Regardless, it is not possible to account for baseline hearing levels in the ISO model.[101] This is likely the reason that our mixed models consistently predicted higher hearing thresholds than the ISO model, and highlights an important weakness in the ISO model.

Chapter 6 – Summary, Conclusions, and Future Research

This dissertation research focused on improving our ability to assess occupational noise exposures through three separate but complementary projects. The first project, summarized in chapters 2 and 3, evaluated the feasibility of using new technologies to reduce the cost and technical barriers associated with collecting exposure information. The motivation for that project was to increase the total number of noise measurements available to researchers and occupational health practitioners, particularly in occupations where few data are available. The existence of large, previously-collected noise exposure datasets for common occupations made it possible to complete the second project of this dissertation, construction of a large job exposure matrix (JEM) that provides estimated noise exposure levels for nearly all occupations in the US. This JEM represents a tool for surveillance of trends in noise levels, as well as for targeting of specific high-exposure occupations for additional assessment and control. The third and final project in this dissertation examined the ability of two different noise metrics (those specified by the Occupational Safety and Health Administration, OSHA, and the National Institute for Occupational Safety and Health, NIOSH) predicted hearing loss in a cohort of construction workers using both linear mixed models and recognized hearing loss models.[101,136] While these three projects are very distinct, the underlying goal of each of them is to improve exposure assessment methods for assessing the relationship between occupational noise exposure and NIHL.

Project 1

The first project of this dissertation involved evaluating the accuracy of smart devices to measure occupational noise. The results of this project showed that under some circumstances smart devices can be used to make accurate noise measurements, and adds to the growing evidence that these devices have utility for measuring noise exposure.[20,151,152] This finding has major implications for assessing occupational and community noise exposures, as it is estimated that 72% of Americans, and 45% of the world's entire population, use a smartphone.[153] Wealthier countries currently have a much higher percentage of smartphone users, many areas in Asia and Africa have begun to use the technology as well.[153] While it is unrealistic to expect even the majority of the billions of smartphone users to measure noise with their devices, having this capability distributed among so many people makes it possible – for the a first time – to "crowd-source" exposure measurements and obtain reasonably accurate results. This has already occurred on a minor scale in several cities where smart device microphones and GPS capabilities are used to produce noise maps of the city, [67,73–76] but these previous efforts have been hampered by uncertainties regarding the accuracy of the collected data.

In the workplace, smart devices can be used by concerned workers to demonstrate evidence of possible overexposure to noise and trigger a more formal exposure assessment by an industrial hygienist. There is also great potential for these apps to serve as an educational tool for workers by providing feedback and instruction on when and how to wear hearing protection. The apps evaluated during this dissertation research had to be purchased from the developer; this creates a financial barrier that may prevent workers from using higher-quality apps. However, NIOSH recently released their version of a noise measurement app for iOS. This app has the advantage of being both free and supported by a government agency with expertise in noise assessment, and offers useful options such as a calibration feature, which is absent on many commercially-produced apps.[154] While the requirement of an external microphone to make accurate measurements is still an outstanding issue, it is worth noting that these microphones can be acquired for as little as $20, which is still far less than the cost to purchase a type 2 SLM.

Despite the progress made in applying technology to noise exposure assessment, there are still avenues for further research. The majority of apps tested have been on Apple's iOS platform, despite the fact the Android platform makes up a larger market share of smart devices.[155] This is due to the fact that the Android platform is used by a variety of device manufacturers, resulting in a large number of devices with differing components. This diversity in Android hardware has made it difficult to formally assess the large variety of apps available on that platform. However, the use of an external microphone offers the opportunity to standardize noise measurements, providing that an Android app that allows users to select an external microphone could be developed in the future. Future researchers investigating the feasibility of using Android devices will be able to use the testing procedures developed during this dissertation research as a template for additional experiments.

There is also the possibility that some apps could, with the user's consent, upload exposure, job, and other meta data to a central database for use by researchers. This possibility raises several important issues regarding privacy, data storage and access, and quality control. In addition, the amount of data that could be received would make it challenging to analyze in a way that would provide any meaningful information. However, the completion of the second project of this dissertation provides a foundation for using and translating large amounts of exposure information into an effective exposure assessment tool.

Project 2

The second project addressed the process of creating a coherent database of noise measurements in order to establish an occupational noise exposure JEM. The process established as part of this dissertation can continue to be used as new data become available, whether from traditional noise measurement instruments or from smart devices. The JEM currently contains over 1,000,000 occupational noise measurements, and represents a powerful exposure assessment tool for researchers. The focus of this dissertation research, development of an imputation model that can be used to estimate noise exposure for almost every job in the US, was critical to populate jobs in the JEM for which no measurement data were available. However, the JEM also makes it possible to conduct analyses of noise exposures for specific industries; we have already done so for the mining industry, and analysis for general industry is underway.[93]

A previous meta-analysis of the data found that there is considerable heterogeneity in exposure measurements obtained from government, industry, and literature sources, and that there is evidence that some sources produce biased estimates.[91] The data we have do not allow us to identify the underlying cause of this bias, but it could be due to differences in sampling strategies used by government agencies and private industry.[156] This issue highlights the limit of using a purely data driven approach to assessing exposure to occupational noise.

To further enhance the exposure estimates provided by the JEM, a measure of frequency of exposure can be assigned to each job title at the broad SOC level by using data from the Bureau of Labor Statistics' (BLS) Occupational Information Network (O*NET) occupational survey. Specifically, the question "How often does this job require working exposed to sounds and noise levels that are distracting or uncomfortable?" (element 4.C.2.b.1.a) provides a continuous response from 0 (never) to 100 (always) that could be used. Because job titles in the JEM are coded using the same system used by the BLS is O*NET, this measure of exposure frequency could easily be integrated in to the JEM, and would provide a measure of an additional aspect of occupational noise exposure.

The validity of the JEM can be assessed in several ways. The simplest way would be to make additional measurements for each job title and compare the newly-collected exposures to the estimated levels for those job titles in the JEM. This would be very time-consuming and costly to do; however, in addition to validating the JEM, this effort would also add additional exposure information to the JEM. It would be more practical to assign individuals from the 2012 National Health and Nutrition Examination Survey (NHANES) an estimated noise exposure based on their reported occupations and duration of employment, and to use statistical modeling and the ISO noise-induced hearing loss prediction models to estimate their expected NIHL based on their occupational exposures. The expected vs. observed audiometric thresholds could then be compared; small differences would suggest high validity of the JEM exposure estimates. The estimated exposures from the JEM could also be used to predict NIHL in occupational cohorts for which audiometric data is available. This would make it possible to validate the exposure estimates for specific job titles that are of interest.

The data that make up the JEM will be freely available for researchers and interested individuals to download. There is also an opportunity to develop an online system where individuals can search for exposure information on specific job titles or industries and retrieve graphical information about exposures over time and across different jobs and industries. This would provide a valuable tool for the public and workers to better understand and conceptualize their noise exposures at work.

The JEM contains exposure measurements made using the Occupational Safety and Health Administration's (OSHA) permissible exposure limit (PEL), action level (AL) and the

National Institute for Occupational Safety and Health's (NIOSH) recommended exposure limit (REL). Because the PEL is the legally enforceable exposure limit, the majority of measurements in the JEM were made according to the PEL criteria.[18] Starting in 1983, the JEM also contains measurements made using the OSHA AL method. However, most other government agencies around the world use a method similar to the NIOSH REL, which was adopted in 1998.[16] There is a debate in the industrial hygiene community as to whether the OSHA or NIOSH criteria for measuring noise exposure better predicts the risk of NIHL. This is an important consideration for using the JEM as an exposure assessment tool. If one method is found to be superior to the other, then future data collection efforts for the JEM should emphasize collecting measurements made using the superior method.

Project 3

The third and final project in this dissertation research focused on evaluating whether noise measurements made using the NIOSH REL (L_{EQ}) or OSHA PEL (L_{AVG}) method produced better estimates of NIHL in a cohort of construction workers who were followed for a maximum of ten years. To do this, linear mixed models were constructed predicting hearing levels at 0.5, 1, 2,3,4, 6, and 8 kHz using the two exposure metrics to calculate cumulative exposure. Two sets of these models were run: the first set included a covariate controlling for baseline hearing threshold levels (HTLs), while the second did not include this covariate, but instead considered the baseline HTLs as an additional repeated measurement. Model fit was evaluated by comparing the AICs between equivalent L_{EQ} and L_{AVG} models. In most cases the L_{EQ} models had the lower (better) AIC, this was especially true at the hearing frequencies more sensitive to hearing loss (i.e. 3, 4, 6 kHz).

The predictions from the mixed models were also compared to the equivalent ISO NIHL model predictions. In all cases the ISO model predicted far less hearing loss than what was observed in the cohort. This is likely due to the fact that the ISO model assumes that the individuals have not experienced any measurable hearing loss prior to their exposure, which was not the case for the cohort; workers in the cohort entered the study with an average hearing threshold level of 9.3, 13.1, and 19.3 dB at 3, 4, and 6 kHz respectively. However, the mixed models using the L_{EQ} produced NIHL estimates closer to the equivalent ISO model than the mixed models using the L_{AVG}.

These results provide evidence that the L_{EQ} is a better metric for measuring noise exposure and estimating the risk of NIHL than the L_{AVG} metric. However, the difference between these two metrics is small. Similar research in a larger cohort of workers is needed to determine if a more pronounced difference can be identified. Additional research should also examine the effect of the "peakiness" of noise exposure on NIHL risk. A recent literature review concluded that some combination of the L_{EQ} and a measure of peakiness could produce more accurate estimates of NIHL.[148] When a measure of peakiness was added to the mixed models in this project, the AICs decreased (improved) substantially for all the models regardless of whether the L_{EQ} or L_{AVG} was used, although the L_{EQ} models still generally had lower AIC values. This suggests that the peakiness measure improved the fits of the model, but further research is needed to determine how a measure of noise peakiness should be constructed. Many researchers have used the ratio of the L_{MAX} to the L_{EQ} or L_{AVG} as a measure of noise peakiness. However, there is little evidence that this metric effectively captures the sharpness of the peak of (kurtosis) of an individual's occupational noise exposure. Regardless of what measure is used, there is evidence to suggest that noise peakiness is an important consideration when assessing the risk of NIHL.

The results of these three projects have improved our ability to assess occupational noise exposure and further elucidate the relationship between noise exposure and NIHL. The completion of these projects has also opened up new avenues of research. The availability of apps changes very quickly, and while the NIOSH app brings some stability to the iOS app marketplace, hardware changes necessitate constant re-evaluation of these apps' performance. This can be done using the method developed in chapters 2 and 3 of this dissertation. Data collected by smart devices and traditional noise measurement instruments can be integrated into the JEM to improve exposure estimates which can be validated in epidemiological studies. Finally, as the amount of exposure data increases it will increase the power of statistical models to detect if there is a difference in NIHL estimates using the L_{AVG} or L_{EQ}. The pursuit of these new avenues of research will further increase our understanding of noise exposure and NIHL.

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Appendences

Appendix 1. The Imputation Process

The imputation procedure

The unknown quantities in our system include the broad SOC means $\theta_{ij}^{obs}, i = 1, \dots, I; j = 1, \dots, n_i^{obs}, \theta_{ik}^{mis}, i = 1, \dots, I; k = 1, \dots, n_i^{mis}$, the major SOC means $\theta_i, i = 1, \dots, I$, the population mean μ, the within major SOC sampling variability σ^2 and the between major SOC sampling variability τ^2. Joint posterior inference for these parameters can be made by constructing a Gibbs sampler which approximates the posterior distribution $p(\theta_{11}^{obs}, \dots, \theta_{In_I}^{obs}, \theta_{11}^{mis}, \dots, \theta_{In_I}^{mis}, \theta_1, \dots, \theta_I, \mu, \tau^2, \sigma^2 | observed\ data)$:

$$p\left(\theta_{11}^{obs}, \dots, \theta_{In_I}^{obs}, \theta_{11}^{mis}, \dots, \theta_{In_I}^{mis}, \theta_1, \dots, \theta_I, \mu, \tau^2, \sigma^2 \middle| observed\ data\right)$$

$$\propto p\left(observed\ data \middle| \theta_{11}^{obs}, \dots, \theta_{In_I}^{obs}, \theta_{11}^{mis}, \dots, \theta_{In_I}^{mis}, \theta_1, \dots, \theta_I, \mu, \tau^2, \sigma^2\right). \left\{\prod_{i=1}^{I}\prod_{j=1}^{n_i^{obs}} p(\theta_{ij}^{obs}|\theta_i, \sigma^2)\right\}$$

$$\cdot \left\{\prod_{i=1}^{I}\prod_{k=1}^{n_i^{mis}} p(\theta_{ik}^{obs}|\theta_i, \sigma^2)\right\} \cdot \left\{\prod_{i=1}^{I} p(\theta_i|\mu, \tau^2)\right\} \cdot \pi(\mu) \cdot \pi(\tau^2) \cdot \pi(\sigma^2)$$

Collecting the terms that depend on θ_{ij}^{obs} shows that the full conditional distribution of θ_{ij}^{obs} must be proportional to

$$\left(\theta_{ij}^{obs} \middle| observed\ data, all\ other\ para\right) \propto \exp\left(-\frac{\left(Y_{ij}^{obs} - \theta_{ij}^{obs}\right)^2}{2\frac{\left(s_{ij}^{obs}\right)^2}{n_{ij}^{obs}}}\right) \cdot \exp\left(-\frac{\left(\theta_{ij}^{obs} - \theta_i\right)^2}{2\sigma^2}\right)$$

After some calculations, we find that conditional on σ^2 and θ_i, θ_{ij}^{obs} must be conditionally independent of other θ_{ij}^{obs} as well as independent of the data from broad SOCs other than ij.

$$\theta_{ij}^{obs} \sim N\left(\mu_{ij}^{obs}, (\sigma_{ij}^{obs})^2\right)$$

where $\mu_{ij}^{obs} = \dfrac{Y_{ij}^{obs}\sigma^2 + \theta_i\frac{\left(s_{ij}^{obs}\right)^2}{n_{ij}^{obs}}}{\sigma^2 + \frac{\left(s_{ij}^{obs}\right)^2}{n_{ij}^{obs}}}$ and $(\sigma_{ij}^{obs})^2 = \dfrac{\frac{\left(s_{ij}^{obs}\right)^2}{n_{ij}^{obs}}\sigma^2}{\left(\sigma^2 + \frac{\left(s_{ij}^{obs}\right)^2}{n_{ij}^{obs}}\right)}$

The conditional distribution of θ_{ik}^{mis} will be normal distribution

$$\theta_{ik}^{mis} \sim N(\theta_i, \sigma^2)$$

The conditional distribution of θ_i is also normal distribution

$$\theta_i \sim N(\mu_i, \tau_i^2)$$

where $\mu_i = \frac{\mu\sigma^2+\sum_{j=1}^{n_i^{obs}} \theta_{ij}^{obs}\tau^2+\sum_{k=1}^{n_i^{mis}} \theta_{ik}^{mis}\tau^2}{n_i^{obs}\tau^2 + n_i^{mis}\tau^2 + \sigma^2}$ and $\tau_i^2 = \frac{\sigma^2\tau^2}{n_i^{obs}\tau^2 + n_i^{mis}\tau^2 + \sigma^2}$

The conditional distribution of μ is normal distribution

$$\mu \sim N(\frac{\sum_{i=1}^{I}\theta_i\gamma_0^2 + \mu_0\tau^2}{I\gamma_0^2 + \tau^2}, \frac{\tau^2\gamma_0^2}{I\gamma_0^2 + \tau^2})$$

The conditional distribution of τ^2 will be inverse gamma distribution

$$\tau^2 \sim Inv - Gamma(\frac{I+\eta_0}{2}, \frac{\sum_{i=1}^{I}(\theta_i-\mu)^2 + \eta_0\tau_0^2}{2})$$

The conditional distribution of σ^2 will be inverse gamma distribution

$$\sigma^2 \sim Inv - Gamma(\frac{\sum_{i=1}^{I} n_i^{obs} + \sum_{i=1}^{I} n_i^{mis} + \upsilon_0}{2}, \frac{\sum_{i=1}^{I}\sum_{j=1}^{n_i^{obs}}\left(\theta_{ij}^{obs}-\theta_i\right)^2 + \sum_{i=1}^{I}\sum_{k=1}^{n_i^{mis}}\left(\theta_{ik}^{mis}-\theta_i\right)^2 + \upsilon_0\sigma_0^2}{2})$$

Posterior approximation proceeds by iterative sampling of each unknown quantity from its full conditional distribution. First we choose the number of iterations S to be 10000 and decide starting values for each of these parameters. Given a current state of the unknowns $\left\{\theta_{11}^{obs(s)}, \dots, \theta_{In_I}^{obs(s)}, \theta_{11}^{mis(s)}, \dots, \theta_{In_I}^{mis(s)}, \theta_i^{(s)}, \mu^{(s)}, \tau^{2(s)}, \sigma^{2(s)}\right\}$, a new state is generated as follows:

1. Posterior step: sample $\theta_i^{(s+1)}, i = 1, \dots, I$ from $\theta_i|\mu^{(s)}, \theta_{i1}^{obs(s)}, \dots, \theta_{in_i}^{obs(s)}, \theta_{i1}^{mis(s)}, \dots, \theta_{in_i}^{mis(s)}, \tau^{2(s)}, \sigma^{2(s)}$ based on its full conditional distribution
2. Posterior step: sample $\mu^{(s+1)}$ from $\mu|\theta_1^{(s+1)}, \dots, \theta_I^{(s+1)}, \tau^{2(s)}$
3. Posterior step: sample $\tau^{2(s+1)}$ from $\tau^2|\theta_1^{(s+1)}, \dots, \theta_I^{(s+1)}, \mu^{(s+1)}$
4. Posterior step: sample $\sigma^{2(s+1)}$ from $\sigma^2|\theta_{11}^{obs(s)}, \dots, \theta_{In_I}^{obs(s)}, \theta_{11}^{mis(s)}, \dots, \theta_{In_I}^{mis(s)}, \theta_1^{(s+1)}, \dots, \theta_I^{(s+1)}$
5. Posterior step: sample $\theta_{ij}^{obs(s+1)}, i = 1, \dots, I, j = 1, \dots, n_i^{obs}$ from $\theta_{ij}^{obs}|\theta_i^{(s+1)}, \sigma^{2(s+1)}$
6. Imputation step: sample $\theta_{ij}^{mis(s+1)}, i = 1, \dots, I, j = 1, \dots, n_i^{mis}$ from $\theta_{ij}^{mis}|\theta_i^{(s+1)}, \sigma^{2(s+1)}$

Appendix 2. Exposure Estimates from Imputation Model

Major SOC	Major SOC Title	Broad SOC	Broad SOC Title	Mean (dBA)	Standard Deviation	2.5% quantile	97.5% quantile
11-0000	management occupations	11-1010	chief executives	84.8	1.57	81.78	87.94
11-0000	management occupations	11-1020	general and operations managers	81.8	4.92	72.32	91.67
11-0000	management occupations	11-1030	legislators	82.0	4.87	72.46	91.57
11-0000	management occupations	11-2010	advertising and promotions managers	82.0	4.85	72.42	91.52
11-0000	management occupations	11-2020	marketing and sales managers	82.1	4.9	72.28	91.33
11-0000	management occupations	11-3010	administrative services managers	82.1	4.95	72.25	92.18
11-0000	management occupations	11-3020	computer and information systems managers	77.0	3.73	69.56	84.33
11-0000	management occupations	11-3030	financial managers	82.0	5	72.21	91.76
11-0000	management occupations	11-3050	industrial production managers	86.3	0.3	85.73	86.89
11-0000	management occupations	11-3060	purchasing managers	81.9	4.99	72.31	91.47
11-0000	management occupations	11-3070	transportation, storage, and distribution managers	81.6	0.44	80.72	82.46
11-0000	management occupations	11-3110	compensation and benefits managers	82.0	5.07	71.67	92.22
11-0000	management occupations	11-3120	human resources managers	81.9	4.83	72.46	91.31
11-0000	management occupations	11-3130	training and development managers	82.0	4.89	72.61	91
11-0000	management occupations	11-9010	farmers, ranchers, and other agricultural managers	92.4	0.47	91.49	93.31
11-0000	management occupations	11-9020	construction managers	81.9	4.98	72.41	91.68

11-0000	management occupations	11-9030	education administrators	81.9	3.43	75.15	88.7
11-0000	management occupations	11-9040	architectural and engineering managers	81.8	4.97	72.5	92.02
11-0000	management occupations	11-9050	food service managers	81.9	5	72.51	92.17
11-0000	management occupations	11-9060	funeral service managers	81.9	4.97	71.83	91.21
11-0000	management occupations	11-9070	gaming managers	77.0	2	72.97	80.86
11-0000	management occupations	11-9080	lodging managers	81.8	5.04	71.62	91.66
11-0000	management occupations	11-9110	medical and health services managers	78.7	2.86	73.28	84.36
11-0000	management occupations	11-9120	natural sciences managers	77.3	3.72	70.08	84.37
11-0000	management occupations	11-9130	postmasters and mail superintendents	82.1	5.02	72.03	91.64
11-0000	management occupations	11-9150	social and community service managers	81.8	4.98	72.02	91.26
11-0000	management occupations	11-9160	emergency management directors	82.0	5.1	71.99	91.82
11-0000	management occupations	11-9190	miscellaneous managers	82.0	4.96	71.97	91.6
13-0000	business and financial operations occupations	13-1010	agents and business managers of artists, performers, and athletes	81.5	5.14	71.29	91.24
13-0000	business and financial operations occupations	13-1020	buyers and purchasing agents	77.6	2.1	73.43	81.83
13-0000	business and financial operations occupations	13-1030	claims adjusters, appraisers, examiners, and investigators	81.2	5.14	71.22	91.29
13-0000	business and financial operations occupations	13-1040	compliance officers	92.8	1.89	89.22	96.55
13-0000	business and financial operations occupations	13-1050	cost estimators	81.5	5.03	71.31	91.37
13-0000	business and financial	13-1070	human resources workers	77.9	2.94	72.1	83.48

	operations occupations						
13-0000	business and financial operations occupations	13-1080	logisticians	81.4	5.08	71.5	91.35
13-0000	business and financial operations occupations	13-1110	management analysts	81.4	5.1	71.17	91.23
13-0000	business and financial operations occupations	13-1120	meeting, convention, and event planners	81.6	5.11	71.19	91.37
13-0000	business and financial operations occupations	13-1130	fundraisers	81.5	5.14	71.16	91.23
13-0000	business and financial operations occupations	13-1140	compensation, benefits, and job analysis specialists	81.4	5.15	71.05	91.68
13-0000	business and financial operations occupations	13-1150	training and development specialists	74.6	0.61	73.43	75.8
13-0000	business and financial operations occupations	13-1160	market research analysts and marketing specialists	81.5	5.27	70.84	91.47
13-0000	business and financial operations occupations	13-1190	miscellaneous business operations specialists	81.3	5.03	71.28	90.96
13-0000	business and financial operations occupations	13-2010	accountants and auditors	82.2	3.09	76.36	88.55
13-0000	business and financial operations occupations	13-2020	appraisers and assessors of real estate	81.4	5.19	70.83	91.44
13-0000	business and financial operations occupations	13-2030	budget analysts	81.5	5.18	71.8	91.88
13-0000	business and financial operations occupations	13-2040	credit analysts	81.4	5.07	71.47	90.78

13-0000	business and financial operations occupations	13-2050	financial analysts and advisors	81.4	5.16	71.56	91.84
13-0000	business and financial operations occupations	13-2060	financial examiners	81.3	5.21	71.24	91.52
13-0000	business and financial operations occupations	13-2070	credit counselors and loan officers	81.2	4.88	71.87	90.88
13-0000	business and financial operations occupations	13-2080	tax examiners, collectors and preparers, and revenue agents	81.4	5.07	71.95	91.37
13-0000	business and financial operations occupations	13-2090	miscellaneous financial specialists	81.4	5.22	70.91	91.95
15-0000	computer and mathematical occupations	15-1110	computer and information research scientists	80.2	5.17	69.89	90.25
15-0000	computer and mathematical occupations	15-1120	computer and information analysts	81.5	3.08	75.56	87.57
15-0000	computer and mathematical occupations	15-1130	software developers and programmers	79.2	2.62	73.93	84.39
15-0000	computer and mathematical occupations	15-1140	database and systems administrators and network architects	80.3	5.29	70.13	91.31
15-0000	computer and mathematical occupations	15-1150	computer support specialists	80.5	5.19	70.08	90.37
15-0000	computer and mathematical occupations	15-1190	miscellaneous computer occupations	78.2	1.98	74.34	82.04
15-0000	computer and mathematical occupations	15-2010	actuaries	80.5	5.27	70.38	90.54
15-0000	computer and mathematical occupations	15-2020	mathematicians	80.4	5.2	69.95	90.71
15-0000	computer and mathematical occupations	15-2030	operations research analysts	79.6	3.17	73.41	85.65
15-0000	computer and mathematical occupations	15-2040	statisticians	80.3	5.34	69.89	90.62

15-0000	computer and mathematical occupations	15-2090	miscellaneous mathematical science occupations	80.5	5.19	70.73	90.92
17-0000	architecture and engineering occupations	17-1010	architects, except naval	81.0	4.93	71.66	90.95
17-0000	architecture and engineering occupations	17-1020	surveyors, cartographers, and photogrammetrists	77.4	1.26	75.05	79.86
17-0000	architecture and engineering occupations	17-2010	aerospace engineers	76.7	3.57	70.01	83.57
17-0000	architecture and engineering occupations	17-2020	agricultural engineers	85.1	0.5	84.15	86.08
17-0000	architecture and engineering occupations	17-2030	biomedical engineers	81.3	4.93	72	91.39
17-0000	architecture and engineering occupations	17-2040	chemical engineers	81.3	4.99	71.58	90.91
17-0000	architecture and engineering occupations	17-2050	civil engineers	81.4	4.92	71.95	91.17
17-0000	architecture and engineering occupations	17-2060	computer hardware engineers	81.1	5.06	71.39	91.13
17-0000	architecture and engineering occupations	17-2070	electrical and electronics engineers	81.1	4.91	71.47	90.78
17-0000	architecture and engineering occupations	17-2080	environmental engineers	80.8	1.3	78.25	83.3
17-0000	architecture and engineering occupations	17-2110	industrial engineers, including health and safety	81.1	1.41	78.21	83.91
17-0000	architecture and engineering occupations	17-2120	marine engineers and naval architects	81.3	4.97	71.55	91.24

17-0000	architecture and engineering occupations	17-2130	materials engineers	81.1	4.85	71.67	90.78
17-0000	architecture and engineering occupations	17-2150	mining and geological engineers, including mining safety engineers	80.1	0.44	79.29	81
17-0000	architecture and engineering occupations	17-2160	nuclear engineers	85.9	2.8	80.43	91.34
17-0000	architecture and engineering occupations	17-2170	petroleum engineers	81.2	5.01	71.39	90.65
17-0000	architecture and engineering occupations	17-2190	miscellaneous engineers	81.2	5.06	71.32	91.29
17-0000	architecture and engineering occupations	17-3010	drafters	81.3	4.86	71.58	90.36
17-0000	architecture and engineering occupations	17-3020	engineering technicians, except drafters	79.9	0.09	79.72	80.1
17-0000	architecture and engineering occupations	17-3030	surveying and mapping technicians	82.5	2.99	76.61	88.22
19-0000	life, physical, and social science occupations	19-1010	agricultural and food scientists	81.4	5.14	71.39	91.55
19-0000	life, physical, and social science occupations	19-1020	biological scientists	81.5	4.96	72.06	91.41
19-0000	life, physical, and social science occupations	19-1030	conservation scientists and foresters	88.5	2.74	83.18	93.97
19-0000	life, physical, and social science occupations	19-1040	medical scientists	81.5	5.05	71.08	91.24
19-0000	life, physical, and social	19-1090	miscellaneous life scientists	76.5	0.72	75.07	77.88

	science occupations						
19-0000	life, physical, and social science occupations	19-2010	astronomers and physicists	81.4	5.16	71.41	91.29
19-0000	life, physical, and social science occupations	19-2020	atmospheric and space scientists	81.4	5.04	71.29	91.77
19-0000	life, physical, and social science occupations	19-2030	chemists and materials scientists	79.6	3.47	72.95	86.5
19-0000	life, physical, and social science occupations	19-2040	environmental scientists and geoscientists	81.5	5.06	71.73	91.31
19-0000	life, physical, and social science occupations	19-2090	miscellaneous physical scientists	81.3	5.05	71.48	91.05
19-0000	life, physical, and social science occupations	19-3010	economists	81.5	5.04	71.22	91.4
19-0000	life, physical, and social science occupations	19-3020	survey researchers	81.4	4.99	71.8	91.39
19-0000	life, physical, and social science occupations	19-3030	psychologists	81.4	5.17	71.52	91.75
19-0000	life, physical, and social science occupations	19-3040	sociologists	81.6	5.15	71.64	91.39
19-0000	life, physical, and social science occupations	19-3050	urban and regional planners	81.5	5.17	71.31	91.3
19-0000	life, physical, and social science occupations	19-3090	miscellaneous social scientists and related workers	81.4	4.97	71.7	91.26
19-0000	life, physical, and social science occupations	19-4010	agricultural and food science technicians	84.0	1.57	80.77	86.97

19-0000	life, physical, and social science occupations	19-4030	chemical technicians	79.6	0.32	78.98	80.23
19-0000	life, physical, and social science occupations	19-4040	geological and petroleum technicians	81.5	5.05	71.45	91.65
19-0000	life, physical, and social science occupations	19-4050	nuclear technicians	81.4	5.09	71.38	91.31
19-0000	life, physical, and social science occupations	19-4060	social science research assistants	81.4	5.13	71.33	91.2
19-0000	life, physical, and social science occupations	19-4090	miscellaneous life, physical, and social science technicians	79.4	0.7	78.01	80.72
21-0000	community and social service occupations	21-1010	counselors	75.4	3.49	68.55	82.23
21-0000	community and social service occupations	21-1020	social workers	80.6	5.58	69.64	91.43
21-0000	community and social service occupations	21-1090	miscellaneous community and social service specialists	83.3	3.72	76.02	90.97
21-0000	community and social service occupations	21-2010	clergy	80.4	5.57	69.14	91.52
21-0000	community and social service occupations	21-2020	directors, religious activities and education	80.8	5.53	69.92	91.48
21-0000	community and social service occupations	21-2090	miscellaneous religious workers	80.5	5.55	70.1	91.58
25-0000	education, training, and library occupations	25-1010	business teachers, postsecondary	78.7	5.19	68.84	88.94
25-0000	education, training, and	25-1020	math and computer teachers, postsecondary	78.7	5.18	68.76	88.87

	library occupations						
25-0000	education, training, and library occupations	25-1030	engineering and architecture teachers, postsecondary	78.4	5.28	68.13	89.12
25-0000	education, training, and library occupations	25-1040	life sciences teachers, postsecondary	78.5	5.38	67.7	89.39
25-0000	education, training, and library occupations	25-1050	physical sciences teachers, postsecondary	78.4	5.15	68.58	89.07
25-0000	education, training, and library occupations	25-1060	social sciences teachers, postsecondary	78.5	5.28	68.5	89.43
25-0000	education, training, and library occupations	25-1070	health teachers, postsecondary	78.5	5.02	68.62	88.52
25-0000	education, training, and library occupations	25-1080	education and library science teachers, postsecondary	78.4	5.09	68.75	88.83
25-0000	education, training, and library occupations	25-1110	law, criminal justice, and social work teachers, postsecondary	78.5	5.02	68.59	88.74
25-0000	education, training, and library occupations	25-1120	arts, communications, and humanities teachers, postsecondary	78.6	5.21	68.18	89.16
25-0000	education, training, and library occupations	25-1190	miscellaneous postsecondary teachers	78.5	5.14	68.64	88.75
25-0000	education, training, and library occupations	25-2010	preschool and kindergarten teachers	78.6	5.16	68.69	88.31
25-0000	education, training, and library occupations	25-2020	elementary and middle school teachers	78.5	5	68.71	88.28
25-0000	education, training, and library occupations	25-2030	secondary school teachers	81.1	0.79	79.53	82.62

25-0000	education, training, and library occupations	25-2050	special education teachers	78.5	5.16	68.21	88.36
25-0000	education, training, and library occupations	25-3010	adult basic and secondary education and literacy teachers and instructors	85.3	1.68	81.89	88.55
25-0000	education, training, and library occupations	25-3020	self-enrichment education teachers	80.3	4.47	71.8	89.13
25-0000	education, training, and library occupations	25-3090	miscellaneous teachers and instructors	78.6	5.15	68.29	88.67
25-0000	education, training, and library occupations	25-4010	archivists, curators, and museum technicians	78.6	5.16	68.66	89.23
25-0000	education, training, and library occupations	25-4020	librarians	78.7	5.19	68.45	88.58
25-0000	education, training, and library occupations	25-4030	library technicians	61.0	0.67	59.73	62.27
25-0000	education, training, and library occupations	25-9010	audio-visual and multimedia collections specialists	78.7	5.28	68.17	89.25
25-0000	education, training, and library occupations	25-9020	farm and home management advisors	78.6	5.22	68.18	88.71
25-0000	education, training, and library occupations	25-9030	instructional coordinators	78.5	5.22	68.35	88.8
25-0000	education, training, and library occupations	25-9040	teacher assistants	78.7	5.25	68.52	88.66
25-0000	education, training, and library occupations	25-9090	miscellaneous education, training, and library workers	78.6	5.3	68.21	88.96
27-0000	arts, design, entertainment,	27-1010	artists and related workers	84.7	0.76	83.17	86.08

	sports, and media occupations						
27-0000	arts, design, entertainment, sports, and media occupations	27-1020	designers	83.3	5.03	73.3	93.32
27-0000	arts, design, entertainment, sports, and media occupations	27-2010	actors, producers, and directors	83.5	5.3	73.08	93.94
27-0000	arts, design, entertainment, sports, and media occupations	27-2020	athletes, coaches, umpires, and related workers	87.0	1.18	84.74	89.36
27-0000	arts, design, entertainment, sports, and media occupations	27-2030	dancers and choreographers	83.6	4.95	73.88	93.36
27-0000	arts, design, entertainment, sports, and media occupations	27-2040	musicians, singers, and related workers	88.2	1.17	85.85	90.48
27-0000	arts, design, entertainment, sports, and media occupations	27-3020	news analysts, reporters and correspondents	77.5	3.38	70.53	84.08
27-0000	arts, design, entertainment, sports, and media occupations	27-3030	public relations specialists	85.5	1.37	82.7	88.09
27-0000	arts, design, entertainment, sports, and media occupations	27-3040	writers and editors	83.5	5.02	73.68	93.05
27-0000	arts, design, entertainment, sports, and media occupations	27-3090	miscellaneous media and communication workers	83.7	4.93	74.03	93.72
27-0000	arts, design, entertainment, sports, and	27-4010	broadcast and sound engineering	79.9	3.64	72.79	86.83

	media occupations		technicians and radio operators				
27-0000	arts, design, entertainment, sports, and media occupations	27-4020	photographers	83.5	5.04	73.7	93.45
27-0000	arts, design, entertainment, sports, and media occupations	27-4030	television, video, and motion picture camera operators and editors	84.7	3.76	77.21	92.08
27-0000	arts, design, entertainment, sports, and media occupations	27-4090	miscellaneous media and communication equipment workers	83.5	5.16	73.16	93.94
29-0000	healthcare practitioners and technical occupations	29-1010	chiropractors	81.6	4.95	71.59	91.24
29-0000	healthcare practitioners and technical occupations	29-1020	dentists	87.9	1.04	85.88	90
29-0000	healthcare practitioners and technical occupations	29-1030	dietitians and nutritionists	81.5	5.01	72.03	91.11
29-0000	healthcare practitioners and technical occupations	29-1040	optometrists	81.7	4.99	71.94	91.25
29-0000	healthcare practitioners and technical occupations	29-1050	pharmacists	81.5	5.11	71.29	91.18
29-0000	healthcare practitioners and technical occupations	29-1060	physicians and surgeons	86.4	2.77	81.15	91.93
29-0000	healthcare practitioners and technical occupations	29-1070	physician assistants	81.6	5.12	71.5	91.49
29-0000	healthcare practitioners and technical occupations	29-1080	podiatrists	81.6	5.09	71.43	91.45
29-0000	healthcare practitioners	29-1120	therapists	81.5	5.05	71.56	91.53

	and technical occupations						
29-0000	healthcare practitioners and technical occupations	29-1130	veterinarians	85.9	1.51	83.03	88.93
29-0000	healthcare practitioners and technical occupations	29-1140	registered nurses	81.5	4.99	71.53	91.08
29-0000	healthcare practitioners and technical occupations	29-1150	nurse anesthetists	81.5	5.09	71.53	91.42
29-0000	healthcare practitioners and technical occupations	29-1160	nurse midwives	81.5	4.98	71.77	91.69
29-0000	healthcare practitioners and technical occupations	29-1170	nurse practitioners	78.7	4.09	70.9	86.59
29-0000	healthcare practitioners and technical occupations	29-1180	audiologists	81.6	4.88	72.06	91.26
29-0000	healthcare practitioners and technical occupations	29-1190	miscellaneous health diagnosing and treating practitioners	81.4	5.1	71.39	91.64
29-0000	healthcare practitioners and technical occupations	29-2010	clinical laboratory technologists and technicians	81.4	4.9	71.62	91.36
29-0000	healthcare practitioners and technical occupations	29-2020	dental hygienists	81.4	5.02	71.86	91.53
29-0000	healthcare practitioners and technical occupations	29-2030	diagnostic related technologists and technicians	81.3	5.05	71.35	91.37
29-0000	healthcare practitioners and technical occupations	29-2040	emergency medical technicians and paramedics	93.0	2.81	87.58	98.39
29-0000	healthcare practitioners and technical occupations	29-2050	health practitioner support technologists and technicians	71.5	1.09	69.39	73.68

29-0000	healthcare practitioners and technical occupations	29-2060	licensed practical and licensed vocational nurses	71.5	0.96	69.7	73.38
29-0000	healthcare practitioners and technical occupations	29-2070	medical records and health information technicians	81.5	5.15	71.68	91.57
29-0000	healthcare practitioners and technical occupations	29-2080	opticians, dispensing	81.3	4.94	71.88	91.21
29-0000	healthcare practitioners and technical occupations	29-2090	miscellaneous health technologists and technicians	81.6	5.19	71.47	91.76
29-0000	healthcare practitioners and technical occupations	29-9010	occupational health and safety specialists and technicians	76.3	0.77	74.68	77.78
29-0000	healthcare practitioners and technical occupations	29-9090	miscellaneous health practitioners and technical workers	81.7	5.18	71.65	92.45
31-0000	healthcare support occupations	31-1010	nursing, psychiatric, and home health aides	82.1	5.48	71.39	92.87
31-0000	healthcare support occupations	31-2010	occupational therapy assistants and aides	82.0	5.49	70.76	92.58
31-0000	healthcare support occupations	31-2020	physical therapist assistants and aides	82.0	5.56	70.96	92.26
31-0000	healthcare support occupations	31-9010	massage therapists	82.3	5.58	71.46	93.3
31-0000	healthcare support occupations	31-9090	miscellaneous healthcare support occupations	82.3	1.22	79.89	84.56
33-0000	protective service occupations	33-1010	first-line supervisors of law enforcement workers	72.0	0.75	70.52	73.52
33-0000	protective service occupations	33-1020	first-line supervisors of fire fighting and prevention workers	79.8	5.04	70.08	89.66
33-0000	protective service occupations	33-1090	miscellaneous first-line supervisors, protective service workers	79.7	5.02	70.25	89.89

33-0000	protective service occupations	33-2010	firefighters	83.5	1.14	81.33	85.79
33-0000	protective service occupations	33-2020	fire inspectors	79.5	4.95	69.94	89.39
33-0000	protective service occupations	33-3010	bailiffs, correctional officers, and jailers	81.5	0.83	79.96	83.11
33-0000	protective service occupations	33-3020	detectives and criminal investigators	69.0	2.21	64.72	73.25
33-0000	protective service occupations	33-3030	fish and game wardens	79.7	5.06	69.78	89.76
33-0000	protective service occupations	33-3040	parking enforcement workers	79.8	5.07	69.78	89.78
33-0000	protective service occupations	33-3050	police officers	85.4	0.64	84.15	86.6
33-0000	protective service occupations	33-9010	animal control workers	81.1	2.2	76.74	85.38
33-0000	protective service occupations	33-9020	private detectives and investigators	79.7	5.01	69.96	89.63
33-0000	protective service occupations	33-9030	security guards and gaming surveillance officers	81.3	1.29	78.81	83.81
35-0000	food preparation and serving related occupations	35-1010	supervisors of food preparation and serving workers	82.2	2.27	77.74	86.69
35-0000	food preparation and serving related occupations	35-2010	cooks	81.0	1.3	78.57	83.65
35-0000	food preparation and serving related occupations	35-2020	food preparation workers	82.9	0.91	81.12	84.69
35-0000	food preparation and serving related occupations	35-3010	bartenders	84.8	1.09	82.7	86.9

35-0000	food preparation and serving related occupations	35-3020	fast food and counter workers	78.8	1.64	75.69	82.02
35-0000	food preparation and serving related occupations	35-3030	waiters and waitresses	84.8	1.7	81.48	88.21
35-0000	food preparation and serving related occupations	35-3040	food servers, nonrestaurant	82.6	1.21	80.22	84.97
35-0000	food preparation and serving related occupations	35-9010	dining room and cafeteria attendants and bartender helpers	81.6	1.2	79.28	83.92
35-0000	food preparation and serving related occupations	35-9020	dishwashers	86.3	1.08	84.16	88.49
35-0000	food preparation and serving related occupations	35-9030	hosts and hostesses, restaurant, lounge, and coffee shop	82.7	4.72	73.62	92.22
35-0000	food preparation and serving related occupations	35-9090	miscellaneous food preparation and serving related workers	83.3	2.43	78.59	87.91
37-0000	building and grounds cleaning and maintenance	37-1010	first-line supervisors of building and grounds cleaning and maintenance workers	84.5	5.37	73.72	94.69
37-0000	building and grounds cleaning and maintenance	37-2010	building cleaning workers	87.1	0.21	86.67	87.49
37-0000	building and grounds cleaning and maintenance	37-2020	pest control workers	84.4	5.41	73.86	94.82

37-0000	building and grounds cleaning and maintenance	37-3010	grounds maintenance workers	86.9	0.42	86.06	87.75
39-0000	personal care and service occupations	39-1010	first-line supervisors of gaming workers	84.6	5.08	74.69	94.68
39-0000	personal care and service occupations	39-2010	animal trainers	84.5	5.16	74.14	94.62
39-0000	personal care and service occupations	39-2020	nonfarm animal caretakers	83.6	2.16	79.53	87.97
39-0000	personal care and service occupations	39-3010	gaming services workers	89.6	0.96	87.74	91.46
39-0000	personal care and service occupations	39-3020	motion picture projectionists	84.4	4.9	74.77	94.07
39-0000	personal care and service occupations	39-3030	ushers, lobby attendants, and ticket takers	89.6	1.3	87.08	92.05
39-0000	personal care and service occupations	39-3090	miscellaneous entertainment attendants and related workers	84.4	1.44	81.62	87.35
39-0000	personal care and service occupations	39-4010	embalmers	84.4	5.16	73.99	94.31
39-0000	personal care and service occupations	39-4020	funeral attendants	84.6	4.94	74.42	94.37
39-0000	personal care and service occupations	39-4030	morticians, undertakers, and funeral directors	84.7	5.03	75.32	94.9
39-0000	personal care and service occupations	39-5010	barbers, hairdressers, hairstylists and cosmetologists	84.6	2.82	79.03	90.15
39-0000	personal care and service occupations	39-5090	miscellaneous personal appearance workers	84.5	4.99	74.99	94.56
39-0000	personal care and service occupations	39-6010	baggage porters, bellhops, and concierges	80.7	2.4	75.66	85.28
39-0000	personal care and service occupations	39-7010	tour and travel guides	84.6	5.15	74.55	95.01
39-0000	personal care and service occupations	39-9010	childcare workers	83.2	4.08	75.16	91.59

39-0000	personal care and service occupations	39-9020	personal care aides	84.7	5.14	74.77	95
39-0000	personal care and service occupations	39-9040	residential advisors	84.4	5.04	74.33	94.07
39-0000	personal care and service occupations	39-9090	miscellaneous personal care and service workers	84.5	5	75.07	94.17
41-0000	sales and related occupations	41-1010	first-line supervisors of sales workers	82.0	1.24	79.65	84.38
41-0000	sales and related occupations	41-2010	cashiers	77.5	1.52	74.55	80.58
41-0000	sales and related occupations	41-2020	counter and rental clerks and parts salespersons	81.1	5.13	71.07	91.04
41-0000	sales and related occupations	41-2030	retail salespersons	84.1	0.85	82.45	85.81
41-0000	sales and related occupations	41-3010	advertising sales agents	81.2	5.12	71.28	90.82
41-0000	sales and related occupations	41-3020	insurance sales agents	81.0	5.02	71.03	90.82
41-0000	sales and related occupations	41-3030	securities, commodities, and financial services sales agents	81.2	4.99	71.52	91.27
41-0000	sales and related occupations	41-3040	travel agents	81.2	5.11	71.21	90.87
41-0000	sales and related occupations	41-3090	miscellaneous sales representatives, services	81.4	5.04	71.72	91.05
41-0000	sales and related occupations	41-4010	sales representatives, wholesale and manufacturing	74.4	2.64	69.16	79.59
41-0000	sales and related occupations	41-9010	models, demonstrators, and product promoters	81.3	5.21	70.91	91.56
41-0000	sales and related occupations	41-9020	real estate brokers and sales agents	81.3	5.06	71.47	91.27
41-0000	sales and related occupations	41-9030	sales engineers	81.2	5.05	71.28	91.3

41-0000	sales and related occupations	41-9040	telemarketers	81.3	5.04	71.36	91.4
41-0000	sales and related occupations	41-9090	miscellaneous sales and related workers	85.6	0.31	85.04	86.27
43-0000	office and administrative support occupations	43-1010	first-line supervisors of office and administrative support workers	79.8	1.17	77.58	82.15
43-0000	office and administrative support occupations	43-2010	switchboard operators, including answering service	78.7	4.75	69.33	88.07
43-0000	office and administrative support occupations	43-2020	telephone operators	78.7	4.78	69.58	88.39
43-0000	office and administrative support occupations	43-2090	miscellaneous communications equipment operators	85.6	0.94	83.66	87.34
43-0000	office and administrative support occupations	43-3010	bill and account collectors	78.7	4.72	69.35	88.17
43-0000	office and administrative support occupations	43-3020	billing and posting clerks	78.8	4.87	69.6	88.47
43-0000	office and administrative support occupations	43-3030	bookkeeping, accounting, and auditing clerks	83.0	3.55	75.92	89.86
43-0000	office and administrative support occupations	43-3040	gaming cage workers	78.7	4.8	69.39	88.11
43-0000	office and administrative support occupations	43-3050	payroll and timekeeping clerks	75.0	1.55	71.91	78.08
43-0000	office and administrative support occupations	43-3060	procurement clerks	78.9	4.79	69.67	88.21
43-0000	office and administrative support occupations	43-3070	tellers	78.9	4.75	69.46	87.94

43-0000	office and administrative support occupations	43-3090	miscellaneous financial clerks	78.6	4.81	69.62	88.29
43-0000	office and administrative support occupations	43-4010	brokerage clerks	78.8	4.88	69.35	88.4
43-0000	office and administrative support occupations	43-4020	correspondence clerks	78.8	4.9	69.81	88.54
43-0000	office and administrative support occupations	43-4030	court, municipal, and license clerks	78.8	4.89	69.14	88.38
43-0000	office and administrative support occupations	43-4040	credit authorizers, checkers, and clerks	78.8	4.82	69.45	87.72
43-0000	office and administrative support occupations	43-4050	customer service representatives	78.6	0.77	77.18	80.08
43-0000	office and administrative support occupations	43-4060	eligibility interviewers, government programs	78.8	4.85	69.22	88.18
43-0000	office and administrative support occupations	43-4070	file clerks	78.7	4.81	69.41	88.16
43-0000	office and administrative support occupations	43-4080	hotel, motel, and resort desk clerks	80.3	1.18	78.07	82.53
43-0000	office and administrative support occupations	43-4110	interviewers, except eligibility and loan	78.7	4.81	69.26	87.95
43-0000	office and administrative support occupations	43-4120	library assistants, clerical	79.0	4.93	69.18	88.75
43-0000	office and administrative support occupations	43-4130	loan interviewers and clerks	78.8	4.94	69.03	88.38
43-0000	office and administrative	43-4140	new accounts clerks	78.7	4.95	69.16	88.67

	support occupations						
43-0000	office and administrative support occupations	43-4150	order clerks	78.8	4.77	69.34	88.02
43-0000	office and administrative support occupations	43-4160	human resources assistants, except payroll and timekeeping	78.8	4.82	69.14	88.09
43-0000	office and administrative support occupations	43-4170	receptionists and information clerks	78.8	4.78	69.29	87.95
43-0000	office and administrative support occupations	43-4180	reservation and transportation ticket agents and travel clerks	76.8	1.62	73.61	79.93
43-0000	office and administrative support occupations	43-4190	miscellaneous information and record clerks	78.9	4.85	69.46	88.14
43-0000	office and administrative support occupations	43-5010	cargo and freight agents	82.7	0.97	80.78	84.6
43-0000	office and administrative support occupations	43-5020	couriers and messengers	78.8	4.89	69.14	87.85
43-0000	office and administrative support occupations	43-5030	dispatchers	77.1	0.78	75.53	78.56
43-0000	office and administrative support occupations	43-5040	meter readers, utilities	78.8	4.99	69.45	88.7
43-0000	office and administrative support occupations	43-5050	postal service workers	82.2	1.27	79.67	84.72
43-0000	office and administrative support occupations	43-5060	production, planning, and expediting clerks	81.0	2.87	75.15	86.38
43-0000	office and administrative support occupations	43-5070	shipping, receiving, and traffic clerks	77.1	0.42	76.36	77.98

43-0000	office and administrative support occupations	43-5080	stock clerks and order fillers	80.3	0.29	79.73	80.88
43-0000	office and administrative support occupations	43-5110	weighers, measurers, checkers, and samplers, recordkeeping	71.2	0.62	69.98	72.38
43-0000	office and administrative support occupations	43-6010	secretaries and administrative assistants	78.9	4.88	69.69	88.65
43-0000	office and administrative support occupations	43-9010	computer operators	78.9	4.78	69.6	88.4
43-0000	office and administrative support occupations	43-9030	desktop publishers	78.7	4.78	69.26	87.77
43-0000	office and administrative support occupations	43-9040	insurance claims and policy processing clerks	78.7	4.87	69.26	88.53
43-0000	office and administrative support occupations	43-9050	mail clerks and mail machine operators, except postal service	78.7	4.85	69.15	87.88
43-0000	office and administrative support occupations	43-9060	office clerks, general	70.7	1.38	67.98	73.41
43-0000	office and administrative support occupations	43-9070	office machine operators, except computer	81.1	3.07	75.31	87.14
43-0000	office and administrative support occupations	43-9080	proofreaders and copy markers	78.8	4.75	69.74	88.22
43-0000	office and administrative support occupations	43-9110	statistical assistants	77.5	0.79	75.89	78.99
43-0000	office and administrative support occupations	43-9190	miscellaneous office and administrative support workers	73.3	1.08	71.22	75.38
45-0000	farming, fishing, and	45-1010	first-line supervisors of	86.6	4.96	76.63	96.54

	forestry occupations		farming, fishing, and forestry workers				
45-0000	farming, fishing, and forestry occupations	45-2010	agricultural inspectors	80.4	1.09	78.35	82.59
45-0000	farming, fishing, and forestry occupations	45-2020	animal breeders	91.9	0.71	90.49	93.25
45-0000	farming, fishing, and forestry occupations	45-2040	graders and sorters, agricultural products	85.6	1.75	82.24	89.03
45-0000	farming, fishing, and forestry occupations	45-2090	miscellaneous agricultural workers	90.9	0.29	90.36	91.48
45-0000	farming, fishing, and forestry occupations	45-3010	fishers and related fishing workers	87.6	1.48	84.67	90.52
45-0000	farming, fishing, and forestry occupations	45-3020	hunters and trappers	86.4	4.94	76.71	96.35
45-0000	farming, fishing, and forestry occupations	45-4010	forest and conservation workers	86.4	4.95	76.78	96.17
45-0000	farming, fishing, and forestry occupations	45-4020	logging workers	89.6	0.5	88.59	90.62
47-0000	construction and extraction occupations	47-1010	first-line supervisors of construction trades and extraction workers	78.3	0.11	78.05	78.47
47-0000	construction and extraction occupations	47-2010	boilermakers	84.3	1.04	82.31	86.42
47-0000	construction and extraction occupations	47-2020	brickmasons, blockmasons, and stonemasons	86.5	0.32	85.83	87.09
47-0000	construction and extraction occupations	47-2030	carpenters	84.7	0.17	84.35	84.99

47-0000	construction and extraction occupations	47-2040	carpet, floor, and tile installers and finishers	87.9	0.68	86.65	89.25
47-0000	construction and extraction occupations	47-2050	cement masons, concrete finishers, and terrazzo workers	87.6	0.31	87	88.22
47-0000	construction and extraction occupations	47-2060	construction laborers	89.0	0.21	88.63	89.45
47-0000	construction and extraction occupations	47-2070	construction equipment operators	86.4	0.23	85.94	86.81
47-0000	construction and extraction occupations	47-2110	electricians	78.3	0.11	78.06	78.49
47-0000	construction and extraction occupations	47-2120	glaziers	84.5	1.22	82.12	86.81
47-0000	construction and extraction occupations	47-2130	insulation workers	84.6	1.42	81.69	87.33
47-0000	construction and extraction occupations	47-2140	painters and paperhangers	82.2	0.93	80.38	84.05
47-0000	construction and extraction occupations	47-2150	pipelayers, plumbers, pipefitters, and steamfitters	82.4	0.15	82.08	82.67
47-0000	construction and extraction occupations	47-2160	plasterers and stucco masons	83.5	4.78	74.39	92.79
47-0000	construction and extraction occupations	47-2170	reinforcing iron and rebar workers	84.9	1.92	81.05	88.72
47-0000	construction and extraction occupations	47-2180	roofers	89.1	0.65	87.85	90.36
47-0000	construction and extraction occupations	47-2210	sheet metal workers	85.1	0.22	84.65	85.48
47-0000	construction and extraction occupations	47-2220	structural iron and steel workers	80.9	0.79	79.37	82.46
47-0000	construction and extraction occupations	47-3010	helpers, construction trades	79.6	0.39	78.84	80.3
47-0000	construction and extraction occupations	47-4010	construction and building inspectors	83.7	4.81	74.32	93.28

47-0000	construction and extraction occupations	47-4020	elevator installers and repairers	83.5	4.8	73.96	92.93
47-0000	construction and extraction occupations	47-4030	fence erectors	83.6	4.87	74.17	93.39
47-0000	construction and extraction occupations	47-4040	hazardous materials removal workers	75.3	1.12	73.24	77.51
47-0000	construction and extraction occupations	47-4050	highway maintenance workers	83.5	4.79	74.3	92.92
47-0000	construction and extraction occupations	47-4060	rail-track laying and maintenance equipment operators	80.5	0.61	79.38	81.74
47-0000	construction and extraction occupations	47-4070	septic tank servicers and sewer pipe cleaners	85.6	1.1	83.48	87.76
47-0000	construction and extraction occupations	47-4090	miscellaneous construction and related workers	81.6	0.57	80.5	82.71
47-0000	construction and extraction occupations	47-5020	earth drillers, except oil and gas	82.3	0.07	82.22	82.48
47-0000	construction and extraction occupations	47-5030	explosives workers, ordnance handling experts, and blasters	85.5	0.21	85.04	85.86
47-0000	construction and extraction occupations	47-5040	mining machine operators	82.7	0.02	82.7	82.76
47-0000	construction and extraction occupations	47-5050	rock splitters, quarry	84.0	0.11	83.81	84.27
47-0000	construction and extraction occupations	47-5060	roof bolters, mining	84.1	0.04	84.04	84.22
47-0000	construction and extraction occupations	47-5070	roustabouts, oil and gas	83.7	4.82	73.81	93.19
47-0000	construction and extraction occupations	47-5080	helpers--extraction workers	83.9	0.07	83.72	84
47-0000	construction and extraction occupations	47-5090	miscellaneous extraction workers	85.1	0.23	84.61	85.5
49-0000	installation, maintenance, and repair occupations	49-1010	first-line supervisors of mechanics,	83.2	0.65	81.85	84.45

49-0000	installation, maintenance, and repair occupations	49-2010	installers, and repairers computer, automated teller, and office machine repairers	83.3	4.83	74.19	92.86
49-0000	installation, maintenance, and repair occupations	49-2020	radio and telecommunications equipment installers and repairers	84.8	0.98	82.97	86.83
49-0000	installation, maintenance, and repair occupations	49-2090	miscellaneous electrical and electronic equipment mechanics, installers, and repairers	77.0	1.62	73.99	80.41
49-0000	installation, maintenance, and repair occupations	49-3010	aircraft mechanics and service technicians	87.2	1.04	85.03	89.19
49-0000	installation, maintenance, and repair occupations	49-3020	automotive technicians and repairers	83.7	0.28	83.21	84.28
49-0000	installation, maintenance, and repair occupations	49-3030	bus and truck mechanics and diesel engine specialists	83.2	1.07	81.11	85.26
49-0000	installation, maintenance, and repair occupations	49-3040	heavy vehicle and mobile equipment service technicians and mechanics	78.8	0.08	78.68	78.98
49-0000	installation, maintenance, and repair occupations	49-3050	small engine mechanics	86.3	1.54	83.27	89.3
49-0000	installation, maintenance, and repair occupations	49-3090	miscellaneous vehicle and mobile equipment mechanics, installers, and repairers	87.4	1.06	85.48	89.49
49-0000	installation, maintenance, and repair occupations	49-9010	control and valve installers and repairers	88.8	2.23	84.53	93.11
49-0000	installation, maintenance,	49-9020	heating, air conditioning, and refrigeration	87.7	1	85.74	89.57

	and repair occupations		mechanics and installers				
49-0000	installation, maintenance, and repair occupations	49-9030	home appliance repairers	83.5	4.88	73.87	92.92
49-0000	installation, maintenance, and repair occupations	49-9040	industrial machinery installation, repair, and maintenance workers	84.6	0.11	84.35	84.77
49-0000	installation, maintenance, and repair occupations	49-9050	line installers and repairers	81.6	0.77	80.08	83.06
49-0000	installation, maintenance, and repair occupations	49-9060	precision instrument and equipment repairers	75.8	2	71.83	79.58
49-0000	installation, maintenance, and repair occupations	49-9070	maintenance and repair workers, general	81.6	0.06	81.5	81.73
49-0000	installation, maintenance, and repair occupations	49-9080	wind turbine service technicians	83.3	4.9	73.63	92.77
49-0000	installation, maintenance, and repair occupations	49-9090	miscellaneous installation, maintenance, and repair workers	84.2	0.61	83.01	85.41
51-0000	production occupations	51-1010	first-line supervisors of production and operating workers	82.2	0.09	81.98	82.33
51-0000	production occupations	51-2010	aircraft structure, surfaces, rigging, and systems assemblers	85.6	4.75	76.4	95.38
51-0000	production occupations	51-2020	electrical, electronics, and electromechanical assemblers	85.1	0.31	84.54	85.72
51-0000	production occupations	51-2030	engine and other machine assemblers	85.3	4.77	75.73	94.51
51-0000	production occupations	51-2040	structural metal fabricators and fitters	86.7	0.18	86.35	87.05
51-0000	production occupations	51-2090	miscellaneous assemblers and fabricators	82.7	0.05	82.59	82.79

51-0000	production occupations	51-3010	bakers	83.9	0.82	82.31	85.57
51-0000	production occupations	51-3020	butchers and other meat, poultry, and fish processing workers	90.6	0.21	90.18	90.98
51-0000	production occupations	51-3090	miscellaneous food processing workers	88.4	0.16	88.12	88.74
51-0000	production occupations	51-4010	computer control programmers and operators	78.6	0.96	76.82	80.51
51-0000	production occupations	51-4020	forming machine setters, operators, and tenders, metal and plastic	91.2	0.27	90.69	91.76
51-0000	production occupations	51-4030	machine tool cutting setters, operators, and tenders, metal and plastic	87.6	0.07	87.45	87.74
51-0000	production occupations	51-4040	machinists	80.9	0.12	80.67	81.16
51-0000	production occupations	51-4050	metal furnace operators, tenders, pourers, and casters	87.9	0.22	87.43	88.29
51-0000	production occupations	51-4060	model makers and patternmakers, metal and plastic	85.1	0.78	83.56	86.67
51-0000	production occupations	51-4070	molders and molding machine setters, operators, and tenders, metal and plastic	88.2	0.21	87.76	88.56
51-0000	production occupations	51-4080	multiple machine tool setters, operators, and tenders, metal and plastic	88.3	0.17	87.96	88.64
51-0000	production occupations	51-4110	tool and die makers	82.1	0.19	81.75	82.48
51-0000	production occupations	51-4120	welding, soldering, and brazing workers	85.0	0.08	84.83	85.13
51-0000	production occupations	51-4190	miscellaneous metal workers and plastic workers	89.2	0.09	88.98	89.35
51-0000	production occupations	51-5110	printing workers	84.0	0.29	83.42	84.58
51-0000	production occupations	51-6010	laundry and dry-cleaning workers	83.2	0.75	81.69	84.65

51-0000	production occupations	51-6020	pressers, textile, garment, and related materials	89.7	0.3	89.05	90.24
51-0000	production occupations	51-6030	sewing machine operators	81.3	1.21	78.88	83.63
51-0000	production occupations	51-6040	shoe and leather workers	89.1	0.45	88.2	89.93
51-0000	production occupations	51-6050	tailors, dressmakers, and sewers	90.8	1.05	88.75	92.73
51-0000	production occupations	51-6060	textile machine setters, operators, and tenders	89.9	0.18	89.56	90.27
51-0000	production occupations	51-6090	miscellaneous textile, apparel, and furnishings workers	88.1	0.27	87.55	88.65
51-0000	production occupations	51-7010	cabinetmakers and bench carpenters	89.4	0.22	89	89.87
51-0000	production occupations	51-7020	furniture finishers	83.5	1.53	80.44	86.48
51-0000	production occupations	51-7030	model makers and patternmakers, wood	80.8	2.88	75.21	86.61
51-0000	production occupations	51-7040	woodworking machine setters, operators, and tenders	92.5	0.07	92.37	92.62
51-0000	production occupations	51-7090	miscellaneous woodworkers	90.1	0.21	89.7	90.54
51-0000	production occupations	51-8010	power plant operators, distributors, and dispatchers	86.7	0.53	85.66	87.68
51-0000	production occupations	51-8020	stationary engineers and boiler operators	86.9	0.76	85.39	88.39
51-0000	production occupations	51-8030	water and wastewater treatment plant and system operators	75.9	0.47	75	76.86
51-0000	production occupations	51-8090	miscellaneous plant and system operators	82.7	0.43	81.87	83.54
51-0000	production occupations	51-9010	chemical processing machine setters, operators, and tenders	83.9	0.13	83.63	84.14
51-0000	production occupations	51-9020	crushing, grinding, polishing, mixing, and blending workers	87.5	0.08	87.32	87.63

51-0000	production occupations	51-9030	cutting workers	85.1	0.13	84.83	85.35
51-0000	production occupations	51-9040	extruding, forming, pressing, and compacting machine setters, operators, and tenders	86.2	0.65	84.9	87.44
51-0000	production occupations	51-9050	furnace, kiln, oven, drier, and kettle operators and tenders	89.6	0.33	89.01	90.27
51-0000	production occupations	51-9060	inspectors, testers, sorters, samplers, and weighers	81.6	0.12	81.39	81.85
51-0000	production occupations	51-9070	jewelers and precious stone and metal workers	85.5	4.93	75.95	94.79
51-0000	production occupations	51-9080	medical, dental, and ophthalmic laboratory technicians	68.6	1.62	65.6	71.8
51-0000	production occupations	51-9110	packaging and filling machine operators and tenders	86.8	0.19	86.42	87.19
51-0000	production occupations	51-9120	painting workers	84.3	0.18	84	84.68
51-0000	production occupations	51-9140	semiconductor processors	85.4	4.85	76.11	95.47
51-0000	production occupations	51-9150	photographic process workers and processing machine operators	85.6	4.78	76.42	94.78
51-0000	production occupations	51-9190	miscellaneous production workers	87.6	0.07	87.5	87.76
53-0000	transportation and material moving occupations	53-1010	aircraft cargo handling supervisors	83.6	4.91	73.9	92.99
53-0000	transportation and material moving occupations	53-1020	first-line supervisors of helpers, laborers, and material movers, hand	86.7	2.41	81.62	91.41
53-0000	transportation and material moving occupations	53-1030	first-line supervisors of transportation and material-moving machine and vehicle operators	78.2	3	72.2	83.73

53-0000	transportation and material moving occupations	53-2010	aircraft pilots and flight engineers	87.6	0.88	85.93	89.37
53-0000	transportation and material moving occupations	53-2020	air traffic controllers and airfield operations specialists	82.6	0.93	80.81	84.46
53-0000	transportation and material moving occupations	53-2030	flight attendants	83.9	4.97	74.2	93.72
53-0000	transportation and material moving occupations	53-3010	ambulance drivers and attendants, except emergency medical technicians	84.7	2.61	79.69	90.03
53-0000	transportation and material moving occupations	53-3020	bus drivers	78.0	2.63	72.69	83.14
53-0000	transportation and material moving occupations	53-3030	driver/sales workers and truck drivers	81.7	0.03	81.64	81.78
53-0000	transportation and material moving occupations	53-3040	taxi drivers and chauffeurs	83.7	4.85	74.34	93
53-0000	transportation and material moving occupations	53-3090	miscellaneous motor vehicle operators	83.7	4.69	74.63	92.77
53-0000	transportation and material moving occupations	53-4010	locomotive engineers and operators	82.1	2.35	77.18	86.59
53-0000	transportation and material moving occupations	53-4020	railroad brake, signal, and switch operators	82.0	1.08	79.89	84.21
53-0000	transportation and material moving occupations	53-4030	railroad conductors and yardmasters	83.6	4.86	73.81	93.32
53-0000	transportation and material moving occupations	53-4040	subway and streetcar operators	83.8	4.8	74.13	92.52
53-0000	transportation and material	53-4090	miscellaneous rail transportation workers	83.8	4.95	73.7	93.48

	moving occupations						
53-0000	transportation and material moving occupations	53-5010	sailors and marine oilers	83.7	4.68	74.53	92.91
53-0000	transportation and material moving occupations	53-5020	ship and boat captains and operators	84.8	0.97	82.88	86.63
53-0000	transportation and material moving occupations	53-5030	ship engineers	84.0	4.93	74.43	93.35
53-0000	transportation and material moving occupations	53-6010	bridge and lock tenders	83.6	4.76	74.3	92.9
53-0000	transportation and material moving occupations	53-6020	parking lot attendants	84.0	4.67	74.67	93.03
53-0000	transportation and material moving occupations	53-6040	traffic technicians	81.9	1.34	79.25	84.53
53-0000	transportation and material moving occupations	53-6050	transportation inspectors	83.6	4.84	73.78	92.48
53-0000	transportation and material moving occupations	53-6060	transportation attendants, except flight attendants	83.1	0.59	81.98	84.27
53-0000	transportation and material moving occupations	53-6090	miscellaneous transportation workers	83.8	4.85	74.2	93.45
53-0000	transportation and material moving occupations	53-7010	conveyor operators and tenders	88.5	0.44	87.63	89.36
53-0000	transportation and material moving occupations	53-7020	crane and tower operators	88.1	0.33	87.48	88.78
53-0000	transportation and material moving occupations	53-7030	dredge, excavating, and loading machine operators	84.5	0.24	83.98	84.93

53-0000	transportation and material moving occupations	53-7040	hoist and winch operators	80.5	1.59	77.26	83.52
53-0000	transportation and material moving occupations	53-7050	industrial truck and tractor operators	86.6	0.17	86.28	86.98
53-0000	transportation and material moving occupations	53-7060	laborers and material movers, hand	84.9	0.07	84.76	85.04
53-0000	transportation and material moving occupations	53-7070	pumping station operators	88.2	1.05	86.14	90.32
53-0000	transportation and material moving occupations	53-7080	refuse and recyclable material collectors	86.2	0.78	84.74	87.78
53-0000	transportation and material moving occupations	53-7110	mine shuttle car operators	79.1	0.37	78.43	79.83
53-0000	transportation and material moving occupations	53-7120	tank car, truck, and ship loaders	79.7	0.29	79.13	80.24
53-0000	transportation and material moving occupations	53-7190	miscellaneous material moving workers	88.5	0.6	87.33	89.66
55-0000	military specific occupations	55-1010	military officer special and tactical operations leaders	77.2	3.33	70.54	83.74
55-0000	military specific occupations	55-2010	first-line enlisted military supervisors	78.8	5.5	68.18	89.09
55-0000	military specific occupations	55-3010	military enlisted tactical operations and air/weapons specialists and crew members	74.5	2.27	70.06	78.86