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Optimising sampling strategies: components of low-back EMG variability in five heavy industries

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ABSTRACT

Background Direct/ measurement of work activities is costly, so researchers need to distribute resources efficiently to elucidate the relationships between exposures and back injury.

Methods This study used data from full-shift electromyography (EMG; N=133) to develop three exposure metrics: mean, 90th percentile and cumulative EMG. For each metric, the components of variance were calculated between- and within-subject, and between-group for four different grouping schemes: grouping by industry (construction, forestry, transportation, warehousing and wood products), by company, by job and by quintiles based on exposures ranked by jobs within industries. Attenuation and precision of simulated exposure–response relationships were calculated for each grouping scheme to determine efficient sampling strategies.

Results As expected, grouping based on exposure quintiles had the highest between-group variances and lowest attenuation, demonstrating the lowest possible attenuation with this data.

Conclusion There is potential for grouping schemes to reduce attenuation, but precision losses should be considered and whenever possible empirical data should be employed to select potential exposure grouping schemes.

What this paper adds

- Direct measurement is expensive and requires efficient allocation of measurement efforts.
- Grouping measurement has been used to reduce the attenuation of exposure–response relationships for chemical exposures but not for low-back electromyography (EMG) exposures.
- Grouping exposures using quintiles based on exposures ranked by jobs within industries demonstrate the optimal attenuation in exposure–response relationships, followed by a priori schemes based on industry, and then job.
- Examining the components of variance of exposure grouping schemes allows selection of the most efficient sampling scheme (that which requires the fewest measurements to achieve target attenuation levels) for epidemiological studies.
- These results will be useful for researchers who are planning a sampling strategy for occupational EMG measurements and for epidemiologists who are looking for ways to group subjects for assigning exposures.

INTRODUCTION

Occupational back injury is an expensive and prevalent problem.[1–4] To reduce the occurrence of back injuries, researchers need a better understanding of exposure–response relationships in the workplace. Previous studies of such relationships have been limited by the quality of the exposure assessment.[5–8] Direct exposure measurement is generally preferred to more subjective measures, but can be expensive and difficult to use at worksites.[9] Therefore, researchers need to use measurement resources efficiently to elucidate the relationships between exposures and the back injury response. The main goal of an efficient epidemiological sampling strategy is to minimise measurement burden while also minimising attenuation of exposure–response relationships resulting from imprecision in exposure measurements. Literature in the last decade or so has focused on using grouping schemes (eg, based on job, company, industry or other grouping factors) that apply the mean exposure of all measurements within a working group to all workers in that group. This makes the most of available data by offering the benefit of a Berkson error structure, in which the attenuation of an exposure–response relationship is less than when each individual is assigned the mean of their own exposure measurements.[10–12] Residual classical error and exposure–response attenuation can be further minimised when between-group variability is large compared to within-group variability.[10 13–16]

Variance components from pilot data[13 16] can be used to find the 'variance ratio' (within-worker variance divided by the between-worker variance) to estimate bias in the regression coefficients given classical measurement error,[17] or to find the 'contrast' between workers or groups (ratio of between-worker/group variability to the sum of within- and between-worker/group variability).[18 19] In ergonomic epidemiology, Burdorf developed formulae to determine study power and the optimal allocation of measures within and between workers.[13] Components of variance have been used in subsequent statistical methods to assess the attenuation of exposure–response relationships and optimisation of exposure grouping for epidemiological studies.[20–22] Variance components and the effect of grouping on exposure–response attenuation have been published for many chemical and biological exposures.[23–26] For physical exposures, within- and between-worker variability has informed efficient sampling strategies for trapezius electromyography (EMG),[27–29] and low-back EMG during normalisation.[30] To our knowledge, no such studies have been conducted on low-back exposures during non-cyclical heavy industrial tasks.

To examine these issues, we selected muscle activity as quantified by EMG as a potential back injury risk factor that can be directly measured. This measure is not without controversy, because to date epidemiological studies relating EMG exposure levels to musculoskeletal health outcomes are sparse, and because EMG can also register some aspects of outcome, eg, muscle fatigue.[31 32] However, EMG has been widely used as a measure of working exposures[29 33–43] and many assume that there is a relationship between increased muscle loading and musculoskeletal strain.[43] Given the complex, multistage path between work tasks, postures and back pain,[8] muscle activity as measured by EMG might be best thought of as an intermediary between external exposures, such as heavy lifting, and injuries to the back. As such, EMG is similar to a biomarker in studies of chemical agents. Here we treat it as a 'biomarker of exposure', one that estimates composite exposures, since it is affected by awkward postures and manual materials handling. These are both exposures common to industrial work and are considered leading risk factors for low back injuries.[44–46]

The current study addresses sampling strategy issues for low-back EMG exposures in heavy industry: (1) What are the components of variance (within-worker, between-worker and between group) when using different grouping schemes and different EMG metrics? (2) Given the components of variance observed in this study, what level of attenuation can be expected in exposure–response relationships? (3) How many measures per subject and subjects per group are recommended for low-back EMG studies in heavy industry?

METHODS

Study sample and worker recruitment

As part of a larger study, the British Columbia Workers' Compensation Board (WCB) identified a random sample of employees in construction, forestry, transportation, wood products and warehousing for whom a worker's compensation back injury claim had been accepted in 2001 and who agreed to be contacted by researchers. Of these workers, 189 were contacted by researchers and 105 (68%) were eligible (working in heavy industry) at the time of contact. Of these, 74 (70%) agreed to be measured and 54 (73%) of their employers agreed to have measurements conducted at the worksite. Prior to measurement, researchers visited each worksite to recruit up to four co-workers of the original WCB-selected worker, bringing the total sample up to 126 individuals. All workers had production jobs without modified duties in heavy industry. Co-workers worked on the same shift as the WCB-selected worker, although they did not necessarily have the same job title. Human subjects procedures were approved by the University of British Columbia's Behavioural Research Ethics Board and participation was entirely voluntary. Set-up and measurements were conducted during regular work time between September 2004 and February 2006.

EMG data collection

Field sampling

Full-shift EMG (ie, EMG measuring muscle activity) was measured using a portable data collection system with on-board memory (ME3000P4/ME3000P8, Mega Electronics, Kuopio, Finland) and disposable Ag-AgCl electrodes (Blue Sensor N-00-S, Ambu, Denmark). Electrodes were placed over the erector spinae at approximately the level of L4/L5, with a 20 mm inter-electrode spacing and a ground electrode with preamplifier placed on the posterior aspect of the iliac crest. Signals were collected at 1000 Hz and filtered internally using an 8–500 Hz band-pass filter. Root-mean-square EMG values were data logged 10 times per second. Data were collected for the full shift excluding breaks (5.5–10.3 h of working time, mean 6.3 h) and downloaded from the portable system onto a laptop computer during breaks.

Of the 126 workers recruited to the study, successful full-shift EMG measurements were made for 92 individual workers. Second measurements were planned for every worker, but due to time constraints and measurement challenges,[9] complete second measurement data were available for only 37% of workers (36 subjects) for a total of 133 worker-days. The average time period between measurement days for the same worker was 93 days, ranging from 1 to 439 days. To check for any significant differences between workers without measures, with single measures or with duplicate measures, one-way ANOVA (with Tukey's post hoc test) was performed for height, weight, age and hours worked per week. χ^2 Tests were performed for sex and industry.

Calibration

As the electrode–skin interface is unique to each worker and measurement session, a submaximal reference contraction was employed to calibrate EMG data collected during the shift. The effect was to standardise EMG voltage across all measurement sessions with a common reference contraction. The reference contraction involved a static 45° forward trunk flexion while holding an 11.5 kg weight in both hands with arms hanging straight down. Trunk flexion was measured using a 12-inch hand-held goniometer (Baseline Instruments, Fabrication Enterprises, Inc, White Plains, USA) with bubble level for vertical alignment. The reference contraction was held for 5 s, and performed twice at the beginning and end of each shift. All EMG data collected during the shift were expressed as a percentage of this reference contraction (%RC) and all EMG exposures are in units of %RC.

EMG exposure metrics

The magnitude of EMG activity was summarised using the mean or 90th percentile (an estimate of peak magnitude). Since the magnitude of EMG activity is not the only important dimension of exposure,[47–49] a measure of cumulative exposure was used to add the effect of exposure duration. Cumulative exposure was calculated as the mean EMG multiplied by the observed working duration. All metrics were tested for normality using visual inspection of histograms and Kolmogorov–Smirnov tests.

Statistical analysis

Exposures were grouped by job title, by company, by industry and by a job+industry grouping scheme to determine the optimal grouping strategy. The job+industry groupings for each metric were developed post hoc by sorting the EMG values of jobs within industries and then grouping them into quintiles, with attention paid to natural breakpoints in the distributions. While job title, company and industry are based on information that is usually available prior to exposure data collection, the job+industry scheme is based on exposure measurements after they are taken. All grouping schemes would be applied to the exposure data prior to any epidemiological analyses. The post hoc job+industry grouping is expected to demonstrate the best-case, least attenuation option for data grouping, and therefore serves as a comparison to the a priori methods.[50]

Summary data were calculated for the four EMG metrics for all data, by industry, by job, and by the job+industry grouping. These exposure summaries and all other analyses were performed using SAS 9.1 and SPSS 18.

Calculating components of variability

The relative contribution to total variance of each of the potential components of variance was calculated by developing a series of random effects or 'null' models using PROC MIXED in SAS. The first model included only subject as a random effect, while four subsequent models included subject and each grouping variable as a random effect: job; company; industry; and job+industry quintiles.

Exposure–response attenuation

The success of each grouping scheme in signalling exposure differences was determined by estimating the attenuation that the grouping scheme would produce in a linear exposure–response relationship based on continuous exposure and outcome measures.[17 23 51] Equation 1[17 51] was used to calculate attenuation without grouping and includes only the between- and within-subject variance components. Equation 2[51] was applied when there was a grouping scheme and adds the between-group variance component.

$$\beta* = \left(\frac{\sigma^2_{BS}}{\sigma^2_{BS} + (\sigma^2_{WS})/n}\right)\beta \tag{1}$$

$$\beta* = \left(\frac{\sigma^2_{BG} + (\sigma^2_{WG})/k}{\sigma^2_{BG} + (\sigma^2_{WG})/k + (\sigma^2_{WS})/kn}\right)\beta \tag{2}$$

where β is the coefficient of the true exposure–response relationship and $\beta*$ is the attenuated coefficient. The ratio in parentheses is the 'attenuation factor', where σ^2_{WS} is the within-subject variance, σ^2_{BS} is the between-subject variance (in cases where there is no grouping scheme), σ^2_{WG} is the within-group variance (in cases where there is a grouping scheme), σ^2_{BG} is the between-group variance, k is the number of subjects per group and n is the number of measurements per subject. In cases where n and k were not constant between groups and subjects, the average number per group or subject was used. The attenuation factor takes values from 0 to 1, and was calculated for all three EMG metrics and all four grouping schemes using the components of variance calculated in the PROC MIXED models. An attenuation factor of 0 means that the exposure–response is fully attenuated to the point that there is no observable relationship. An attenuation factor of 1 means that the true exposure–response relationship is preserved without any attenuation.

In addition, we calculated the SE of β for simulated sampling strategies using variance data from this study and the following formulae from Tielemans *et al*[51]:

$$SE\left(\beta^*\right) = \sqrt{\frac{n\left[\beta\left(\frac{\sigma^2_{WG}\sigma^2_{WS}}{n\sigma^2_{WG}+\sigma^2_{WS}}\right) + \sigma^2_e\right]}{(G-3)\left(n\sigma^2_{WG} + \sigma^2_{WS}\right)}} \tag{3}$$

$$SE\left(\beta^*_1\right) = \sqrt{\frac{\frac{\sigma^2_e}{k}\left[\sigma^2_{BG} + \frac{\sigma^2_{WG}}{k} + \frac{\sigma^2_{WS}}{kn}\right] + \beta^2\left(\sigma^2_{BG} + \frac{\sigma^2_{WG}}{k}\right)\frac{\sigma^2_{WS}}{kn}}{(G-3)\left[\sigma^2_{BG} + \frac{\sigma^2_{WG}}{k} + \frac{\sigma^2_{WS}}{kn}\right]^2}} \tag{4}$$

where β is the slope describing the relationship between measured exposure and a measured continuous health outcome, G is the number of groups and σ^2_e is the variance in the health outcome measure. The SE of β was calculated for mean, 90th percentile and cumulative EMG for two simulated situations: when there is one measurement per individual or four measurements per individual. Unbalanced sampling is common in field studies due to measurement challenges, but unbalanced data deliver less precise estimates and cannot be investigated using equations 1–4. To allow for comparison between grouping schemes, the total number of individual participants is held constant at 744 and allotted to the categories within each grouping scheme in a balanced fashion (ie, the same number of measurements per worker and workers per group). This yields 24 individuals in each of the 31 companies, 31 individuals in each of the 24 job titles, and 149 (rounded up from 148.8) in each industry and job+industry group. The slope β was set to 1.0 to allow comparability between grouping schemes. Workers' self-reported pain data collected at the end of the work shift using questions from the Standardized Nordic Questionnaire[52] were used to supply the variance of the health outcome, σ^2_e. 'Average low back pain in the last 6 months', on a scale of 1–10, was used as a continuous measure; those who reported having no low back pain in the last 6 months were assigned a zero on this scale.

The purpose of this series of analyses was to investigate the effect of grouping scheme on the precision of the exposure–response slope for each EMG metric.

RESULTS

Participant characteristics

There were no significant differences between workers with zero successful EMG measurements, one measurement or two measurements with respect to height, weight, hours worked per week, age, sex or industry. Self-reported pain in the last 6 months had 63.4% of its variability explained by between-subject differences and 36.5% by within-subject differences.

EMG exposure metrics

Visual inspection of the EMG metrics showed approximately normal distributions with a slight tendency towards a right skew, and the Kolmogorov–Smirnov tests showed the distributions were not significantly different than normal distribution (p values of 0.92, 0.117 and 0.111 for mean, 90th percentile and cumulative EMG, respectively), so no transformations of the data were pursued.

The average exposures over all measurement days for all EMG metrics and for each job and industry are listed in table 1. Exposure averages for the job+industry quintiles are shown in table 2.

Components of variability

Within- and between-subject variances and between-group variances for each of the four grouping schemes are listed in table 3. Between-group variance was small for the job, company and industry grouping schemes, but (as might be expected) much higher for the job+industry grouping scheme.

Attenuation and precision of exposure–response relationships

Table 4 shows the attenuation factors for each EMG exposure metric and grouping strategy in this study. Of the grouping schemes, job and company had the lowest attenuation factors, meaning there would be the most attenuation of a linear exposure–response relationship.

Table 1 Industry and job averages (over all person-shifts†) for four EMG exposure metrics

Category	k‡	N†	Mean in %RC (SD)	90th Percentile in %RC (SD)	Cumulative in %RC×h (SD)
All measurements	92	133	39.6 (20.1)	83.8 (36.6)	1069 (589)
All construction	18	26	51.7 (13.6)	107 (26.0)	1043 (350)
Construction carpenter	5	7	49.2 (7.8)	104 (18.6)	965 (244)
Construction labourer	5	7	61.8 (12.7)	127 (24.4)	1067 (130)
Construction supervisor	3	4	53.0 (18.9)	108 (35.9)	1110 (876)
Other construction trades	2	3	35.8 (14.4)	76.4 (14.5)	1002 (79.2)
Other construction*	3	5	47.6 (10.3)	99.9 (19.4)	1101 (188)
All forestry	19	29	43.1 (26.4)	84.4 (41.1)	1264 (625)
Boom man	6	10	30.5 (12.3)	69.6 (29.5)	965 (371)
Faller	3	4	72.3 (30.5)	139 (49.2)	2016 (1246)
Heavy equipment operator	2	3	38.6 (7.8)	87.9 (17.4)	1332 (74.5)
Heavy-duty equipment mechanic	2	4	41.8 (12.5)	80.5 (2.1)	1435 (239)
Logging machinery operators	4	5	26.4 (5.9)	48.8 (4.3)	999 (313)
Other forestry*	2	3	76.2 (53.1)	120 (56.2)	1328 (547)
All wood products	19	26	37.2 (20.4)	79.1 (37.5)	1114 (548)
Cabinet maker	4	6	45.7 (38.5)	94.3 (65.2)	1000 (478)
Forklift operator	6	9	28.9 (11.5)	60.8 (23.3)	1235 (706)
Lumber grader, puller	4	5	37.8 (7.2)	79.7 (15.2)	898 (197)
Papermaking/coating operator	4	5	32.7 (12.7)	74.0 (24.3)	992 (429)
Other wood products*	1	1	68.2 (—)	145 (—)	2202 (—)
All warehousing	14	22	37.7 (20.2)	70.0 (28.1)	931 (604)
Forklift operator	13	20	37.4 (21.0)	80.6 (44.1)	947 (626)
Other warehousing	1	2	42.3 (—)	84.5 (—)	733 (—)
All transportation	22	30	29.0 (12.4)	70.0 (28.1)	967 (716)
Air transport ramp attendants	3	5	29.5 (8.5)	72.6 (16.6)	694 (361)
Automotive mechanic	4	6	36.5 (15.8)	87.2 (32.0)	598 (223.9)
Bus driver	2	2	14.3 (2.4)	35.7 (7.3)	1062 (261)
Ferry worker	3	3	36.7 (9.7)	71.4 (25.2)	1153 (96)
Storekeepers and parts clerks	2	3	36.1 (21.6)	83.5 (62.3)	2243 (278)
Truck driver	3	5	20.1 (6.1)	51.4 (16.2)	970 (204)
Warehouse person	2	3	33.4 (8.1)	81.0 (12.0)	536 (280)
Other transportation*	3	3	27.5 (12.5)	68.1 (30.8)	956 (389)

*Jobs with only one measurement were combined into 'other' categories for the purpose of this table to avoid identifying individuals. All other analyses were performed with these job titles ungrouped.
†Subjects per group×measurement days per subject=total person-shifts.
‡Subjects per group.
EMG, electromyography; %RC, EMG voltage as % of reference contraction.

Table 5 compares the estimated attenuation, β^* and precision, $SE(\beta)$, of the grouping schemes for simulated sampling strategies with one or four measurements on each of 744 workers. Since the total number of workers and measurements is held constant in both scenarios (one or four measures per worker), the differences in attenuation and precision can be attributed solely to the grouping schemes. Naturally, the attenuation was lower when there were four measurement days per subject rather than one. A trade-off between attenuation and precision can be seen for all EMG metrics. The highest precision (lowest $SE(\beta)$ value) of any of the grouping schemes was for individual measures (no grouping scheme); this scheme also had the most attenuation (lowest β^*value), matched in some cases (eg, grouping by job) where the grouping variable accounted for none or very little of the variability in exposure. Job+industry grouping had the least attenuation in every case.

DISCUSSION

Within- and between-worker components of variance

Within-worker variability accounts for those aspects of exposure that vary within a worker over time, such as day-to-day changes in the volume or rate of work, maintenance schedules or alternate tasks. Between-subject differences can include job characteristics and personal characteristics such as sex, body dimensions, age or habits/task techniques. When higher level grouping factors are not taken into account, between-worker and within-worker variance can also be affected by job, company, industry or other group characteristics.

Table 2 Summary of EMG exposure metrics for the job+industry grouping scheme (exposure quintiles based on exposures ranked by jobs within industries)

Quintiles	N*=k×n	Mean (%RC)	90th Percentile (%RC)	Cumulative (%RC×h)
Group 1	29	23.5	47.9	637
Group 2	24	32.2	70.2	887
Group 3	36	36.0	79.2	1046
Group 4	25	40.2	88.9	1349
Group 5	19	58.4	122.3	1581

*Subjects per group×measurement days per subject=total person-shifts.
EMG, electromyography; %RC, EMG voltage as % of reference contraction.

Table 3 The proportions of variance and absolute variance for three EMG exposure metrics accounted for by between-group, between-subject and within-subject components using five different grouping schemes

	Mean EMG	90th Percentile EMG	Cumulative EMG
No grouping			
Between-subject variance (%)	72.4	60.3	60.3
Within-subject variance (%)	27.6	39.7	39.7
Absolute variance (between-subject)	216.2	609	223535
Absolute variance (within-subject)	82.4	401	146920
Grouping by job			
Between-group variance (%)	26.7	17.4	0
Between-subject variance (%)	46.0	44.4	60.3
Within-subject variance (%)	27.3	38.2	39.7
Grouping by company			
Between-group variance (%)	7.3	3.6	4.7
Between-subject variance (%)	65.0	56.7	76.1
Within-subject variance (%)	27.7	39.7	19.2
Grouping by industry			
Between-group variance (%)	11.6	9.7	0
Between-subject variance (%)	60.7	50.5	60.3
Within-subject variance (%)	27.7	39.7	39.7
Grouping by job+industry quintiles			
Between-group variance (%)	46.8	47.8	32.2
Between-subject variance (%)	30.0	17.1	38.3
Within-subject variance (%)	23.2	35.1	29.5

EMG, electromyography.

A number of investigators have observed within-worker variability to be higher than between-worker variability for chemical exposures[53 54] and trunk postures.[55] However, this is not always the case when investigating musculoskeletal risk factors for EMG,[30] as well as for postures.[56] In the current study, all EMG metrics had larger between-worker components (60.3%–72.4%), likely resulting from the highly diverse study population. These results may not be generalisable to a more homogenous sample; if all 133 EMG measurements were within one industry or job, within-worker variance might be a higher proportion of total variance. As seen in table 3, between-worker variance estimates for mean EMG in the 'Grouping by job' scheme is 46.0%, while the within-worker variance is 27.3%. Without grouping, the within-worker variance is slightly higher at 27.6%. Sampling duration may also affect the components of variance. Full-shift direct measurements of exposure are rare in ergonomics. Repeated shorter duration measurements are likely to differ from each other more than those of longer duration because short-term fluctuations are not averaged out, potentially increasing the within-worker variance component.[57 58]

Effect of grouping strategies on components of variance

Typically, between-worker variability increases and between-group variability tends to decrease as workers are aggregated into broader classification groups with more subjects in each group.[59] However, in this study, the between-group variance was lower for job (24 groups with 1–29 people per group) and company (31 groups with 1–8 people per group) than it was for industry and job+industry grouping (both five groups with 19–36 and 22–33 people per group, respectively).

Between-company differences can include factors such as the design of tools and layout of equipment, safety culture, policies surrounding breaks, and incentives or work rate. Company was included as a potential grouping scheme because it is an easily obtained grouping variable which, if efficient, would provide an inexpensive and feasible way to group exposures. However, in the current study between-company differences comprised less than 7.3% of total variability, so these differences were either very small or had little impact on exposure. For mean EMG, grouping by company had the greatest attenuation.

For mean EMG, 'job' grouping had the second highest between-group variance after the job+industry grouping scheme. However, the 'job' and 'industry' components of variance were zero for cumulative EMG. This means that, in this dataset, none of the variability in cumulative exposure was explained by these groupings, instead it was accounted for entirely by within-subject and between-subject differences. In this case, attenuation remains the same but precision decreases considerably, making 'job' and 'industry' undesirable grouping schemes for cumulative EMG. The proportion of variance explained by the job+industry grouping scheme appears to be due to the ordering of exposures to form groups, rather than any intrinsic similarity of the exposures within job+industry groups.

Interestingly, the job+industry scheme that ordered exposures grouped by job titles within industries had a slightly lower within-worker component of variance than other grouping schemes. This is not because the total variance went down, since the number of measurements (and value of measurements) remained the same.

Effect of grouping strategies on attenuation and precision

In addition to individual-level exposures, four different grouping schemes were compared in this study, with the number of subgroups ranging from five to 744 (the latter where each worker comprises his or her own group). As seen in previous studies,[10] as the attenuation decreases (ie, β^* increases), there is less precision indicated by a larger $SE(\beta)$. The largest difference

Table 4 Attenuation factors for EMG exposure–response relationships estimated using each grouping strategy and exposure metric

Grouping strategy	Number of groups	k Per group, mean (range)	Attenuation factors for: Mean	90th percentile	Cumulative
No grouping*	–	–	0.78	0.68	0.74
Grouping by job†	24	3.5 (1–13)	0.89	0.75	0.74‡
Grouping by company†	31	3.1 (2–10)	0.81	0.70	0.87
Grouping by industry†	5	18.4 (14–22)	0.93	0.89	0.74‡
Grouping by job+industry quintiles†	5	18.4 (14–26)	0.98	0.97	0.98

*Calculated using equation 1.
†Calculated using equation 2.
‡Same as no grouping because between-group variance was zero.
EMG, electromyography.

Table 5 Attenuation, β^* and precision, $SE(\beta)$, for a hypothetical linear relationship between a continuous back injury measure and mean, 90th percentile and cumulative EMG with one or four measurements for each of 744 workers

Exposure metric	Grouping strategy	Number of groups	One measurement day per subject			Four measurement days per subject		
			N*	β^*	SE(β)	N*	β^*	SE(β)
Mean	None	744	744	0.708	0.113	2976	0.906	0.126
	Company	31	744	0.939	2.42	2976	0.984	2.42
	Job	24	744	0.968	2.47	2976	0.992	2.46
	Industry	5	744	0.983	3.70	2976	0.996	3.70
	Job+industry	5	744	0.996	3.70	2976	0.999	3.70
90th Percentile	None	744	744	0.599	0.0624	2976	0.857	0.0725
	Company	31	744	0.889	2.42	2976	0.970	2.42
	Job	24	744	0.939	2.46	2976	0.984	2.46
	Industry	5	744	0.971	3.70	2976	0.993	3.70
	Job+industry	5	744	0.993	3.70	2976	0.998	3.70
Cumulative	None	744	744	0.603	0.018	2976	0.859	0.014
	Company	31	744	0.870	1.93	2976	0.964	2.42
	Job	24	744	0.603	1.56	2976	0.859	2.51
	Industry	5	744	0.646	2.07	2976	0.879	3.81
	Job+industry	5	744	0.995	3.45	2976	0.999	3.69

*Subjects per group×measurement days per subject=total person-shifts.
EMG, electromyography.

was between individual grouping, where attenuation was as high as 32%, and job+industry which had almost no attenuation. Standard errors were lower for individual measures than for grouping schemes.

An ideal grouping scheme has both high precision and low attenuation, but there is a trade-off between these factors. Exposure assessment using grouping and a Berkson error structure reduces attenuation of the slope of an exposure—response relationship, but concomitant reductions in the precision of exposure measurements have the potential to render an exposure—response relationship insignificant.[10] The relative effects of reductions in precision compared to strengthening of exposure—response coefficients need to be weighed. In an empirical study of the relationship between wood dust and lung function, the reduction in precision with grouped exposure estimates was small relative to the increase in slope, such that exposure—response relationships were more likely to be statistically significant with grouping than without.[23] Previous simulations by Seixas *et al*[10] show that grouping schemes can produce unbiased estimates of β with lower standard errors than individual measures when within-individual variance is high and between-individual variance is low. In our simulation based on measured EMG, given that the precision of individual measures was estimated to be many orders of magnitude smaller than the precision of any of the grouping schemes, it seems unlikely that grouping schemes will provide a better opportunity to identify a significant relationship, particularly for cumulative EMG.

This trade-off appears to force a choice between being 'precisely wrong' or 'imprecisely right', although some schemes performed relatively well in both attenuation and precision. The job+industry grouping scheme had the least attenuation for all EMG metrics. Similarly, in one of the first studies exploring these methods, electromagnetic field exposures had more contrast between groups when a post hoc job+industry grouping scheme was used.[60] However, it is important to consider the utility of this grouping strategy. Although post hoc grouping based on measured or estimated exposures, as presented here, is common in epidemiology, dividing workers into these same job+industry quintiles a priori in a different sample, let alone different industry or workforce, is unlikely to be as effective as it was here. Study designers can instead develop their own post hoc grouping scheme using empirical data from exposure measurements once they are collected, as done by Kromhout *et al* in their study of brain cancer and electromagnetic fields.[60] The exposure sampling strategy could be developed based on a priori grouping by industry or job, which were the respective runners-up in attenuation and precision, and then the resulting data used to develop a study-specific post hoc grouping. Note that post hoc exposure grouping must still be done blind to the health outcome.

'Company' was a poor grouping scheme since the attenuation was greater than or equal to that of 'job' with no or minimal gains in precision. As a result, this grouping scheme would not be very useful for an epidemiological study of EMG exposures and back injury.

The attenuation and precision of the grouping schemes also varied with EMG exposure metric. Cumulative EMG had poor attenuation performance in the simulation, but the standard errors for cumulative EMG were also low. Mean EMG tended to have lower attenuation than 90th percentile with similar precision. Selection of an EMG metric for an epidemiological study should be based on biomechanically or physiologically plausible relationships with back disorders; highlighting the difference in attenuation and precision of these metrics serves to inform the sampling strategies of any future studies using these metrics.

Limitations

This study considered only one element (variance components) that might influence the choice of sample sizes in exposure studies. Researchers should plan to collect more measurements than those estimated here as there can be considerable challenges in field-based exposure assessment. For example, previously published data have shown that for every 100 worksite visits, one might achieve only 62 successful EMG measurements.[9] Challenges in carrying out measurements seem to be more frequent in very heavy work due to sweating, snagging of EMG cables and awkward positions compromising the data logger.[9] If some groups (such as construction within the industry grouping scheme) have systematically higher occurrences of these critical tasks, then there will be differential underestimation which could affect comparisons between groups.

When choosing target numbers of workers per group and numbers of measurements per worker, it is also prudent to plan to recruit more than required to find the relationship as recruitment also has many challenges. This recruitment method was designed to deliver access to a wide range of work environments and a variety of exposures, and although initial selection of workers with claims was random, obtaining a representative sample was not the primary goal. Given that there were 92 individuals in this study, it seems unlikely that the grouping schemes with 24 (job) or 31 (company) categories are delivering robust estimates of exposure within these categories. In addition, the wide variety of tasks, jobs and work environments seems likely to have increased between-worker variability more than it would be in a single worksite or occupation.

The total variance in this study was quite high due to the inclusion of multiple industries, companies, job titles and individuals, mimicking the variability in exposure that might be observed in a population-based study rather than an industry-based study. If only a subset of this population were selected, the total variability could be expected to decrease and the relative contribution of each of the components might change (eg, if only construction were studied). It should be noted that only 37% of workers had repeated samples and a maximum of two samples were made per worker; this is a small sample on which to base estimates of within-worker variability, and as a result these findings could be unstable.

The mixed modelling methods employed here have several assumptions: observations are assumed to be independent; the dependent variable is also assumed to come from a normal distribution; the dependent variable is assumed to be linearly related to the fixed factors, random factors and covariates; the variance is assumed to be the same in all groups; and within-subject variability is assumed to be the same in all subjects. Workers with claims were randomly selected and the mean time between measures was 39 days, so the measures can be considered independent. The EMG metrics were approximately normal. However, the data in the present study seem to violate some assumptions. The grouping variables did not always account for a large proportion of EMG variability. Most importantly, the within-group and within-worker variability was not equal across groups or workers, respectively. Variability tends to be higher when exposures are higher,[61] as workers with higher exposures have more opportunity to experience high peaks. The exposure means in the current study are different between groups, and the variances also differ between groups. Despite this observation, previous studies have treated data the same way.[19 23]

Here we used attenuation equations developed elsewhere[17 51] for estimating the impact of random measurement error and grouping on the strength of linear exposure—response relationships, that is, those with continuous exposure and outcome measures. Back injury outcomes can include continuous measures such as back pain scales, number of days with pain or number of work days lost due to pain, so a linear exposure—response assumption is reasonable. However, there is no question that dichotomous outcome measures (eg, presence or absence of pain, injury claims, herniated discs) are often used in back injury research, requiring logistic instead of linear regression. To our knowledge, no one has yet modelled attenuation using grouping in logistic regression.

Along with a strong physiological and biomechanical theory,[62–64] a substantial body of literature exists linking posture and working loads with EMG[65–67] and with musculoskeletal outcomes.[44 45] This suggests that an epidemiological study directly linking working EMG exposures and back injury outcome would be a reasonable undertaking. Any future study linking EMG to health outcomes will require an efficient sampling scheme, the investigation of which forms the basis of the present study.

CONCLUSIONS

As expected, the job+industry exposure quintile grouping scheme had the lowest estimated attenuation of exposure—response relationships, followed by industry alone. Although the combined job+industry grouping scheme demonstrates optimal grouping and contrast between groups, it is not available for a priori sample allocation. This study illustrates the potential for grouping schemes to reduce attenuation of an exposure—response relationship, the trade-off between attenuation and precision, and the value of using empirical data to design measurement strategies and select exposure grouping schemes.

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