Validation of an Ergonomics Assessment Method and Identification of Focus Areas through Development of a Novel Statistical Approach for Aggregated Data

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Abstract: Musculoskeletal disorders continue to be a leading source of lost workdays across all industries. Common ergonomics assessment tools may include criteria extraneous to the stresses at specific companies or industries. Therefore, the creation of assessment tools, based on scientifically validated methods, with industry- or company-specific stresses may be of benefit. Privacy regulations (among other factors) may preclude the 1:1 allocation of stresses to health outcomes, prohibiting conventional epidemiological investigation and validation approaches, therefore requiring the use of aggregated data sources. Based on data from the ergonomic assessment tool of interest (Safety and Ergonomics Risk Assessment - SERA) and aggregated data derived from internal insurance reports a statistical method is developed to investigate; 1) the validity of the tool, 2) a prioritization of intervention targets, and 3) the derivation of threshold values for monitoring. The method involves statistical tests used in epidemiological investigations and draws on the iterative modelling approach common to machine learning.

Using the described approach, significant results for known musculoskeletal issues, a prioritization of countermeasure and intervention targets, and threshold values for long-term monitoring were determined. The successful results indicate that the assessment tool investigated is valid. Consequently, the method is generalized such that practitioners can apply it, should they be faced with similarly structured data.

Keywords: logistic regression, ergonomic assessment, musculoskeletal disorders, aggregate data, intervention prioritization, tool validation

Abbreviations:
MSD: musculoskeletal disorder
SERA: Safety and Ergonomics Risk Assessment
NIOSH: National Institute of Occupational Safety and Health
RNLE: Revised NIOSH Lifting Equation
REBA: Rapid Entire Body Assessment
EAWS: European Assembly Worksheet
KIM: Key Indicator Method

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1. Introduction

Work-related MSDs continue to be a leading source of lost workdays and associated costs, across all industries. In 2019 the costs of overexertion, exertion, and repetitive motion in the United States were estimated to exceed 18 billion dollars and comprise 33% of total workplace injury costs (*Liberty Mutual Workplace Safety Index*, 2019). For countries with a high socio-demographic index, the incidence rate of specific work-related MSDs (low back and neck pain) has even shown a slightly

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increasing trend between the years of 1990 and 2019 and are both within the top 25 causes for disability-adjusted life years in 2019 (Vos et al., 2020). Specifically, within automobile manufacturing, rates of work-related MSD symptoms reportedly range from 79% (both genders) to 98% (for women) performing blue-collar manufacturing tasks (Arghami, Kalantari, Ahmadi Kionani, Zanjirani Farahani, & Kamrani, 2016; Ghasemkhani, Aten, & Azam, 2006; Hussain, 2004). Therefore, the assessment of workplaces, identification of high-risk tasks, and implementation of countermeasures to reduce work-related MSDs and their associated risk factors is a high priority in the automobile and other similar manufacturing industries.

The most common risk factors leading to work-related MSDs have been well established and tools have been developed to enable workplace assessments based on those risk factors. This means that practitioners have a plethora of ergonomics assessment tools available to them for assessing workplaces. The preferred tool for ergonomics assessment of workplaces at the company presented here is SERA (Safety and Ergonomics Risk Assessment). The screening tool SERA was designed based on scientifically validated methods with the aim of providing a whole-body ergonomic screening. Additionally, the tool allows for the assessment of the workplace surroundings, mental stresses, and a hazard and risk assessment, although those will not be considered further in this paper. A major advantage of SERA over conventional, widespread, screening methods, e.g. EAWS, KIM, REBA, etc. is the customization to specific stresses, allowing all stresses of modern manufacturing to be covered while disregarding unnecessary stresses. Further, using a web-application-based approach enables SERA both to have an intuitive user interface, data interfaces to workplace planning systems, and maintain a database of stresses for all manufacturing workplaces, thus making comparisons and reports at any level of the organisation feasible and simple. A workplace assessment in SERA is comprised of 13 criteria, 7 of which focus on various dimensions of physical ergonomics, e.g. postures, forces, loads. Each of these 7 ergonomics criteria focusses on a specific body area or type of force/load. All criteria assessments are multidimensional, including at least repetition/frequency and intensity of a given stress. The result of each criterion is both a quantitative risk score and traffic light color (red, yellow, and green, to represent low-, medium-, and high-risk workstations respectively). The overall ergonomics for a workstation is further summarized using the sum of risk scores for the ergonomics criteria and a further rule-based traffic light (see Figure 1). Although SERA (the criteria, body parts, stresses, etc.) is based on well-established ergonomics, there is a strong interest in both further validating the method and using the wealth of information to determine focus areas across all workplaces.

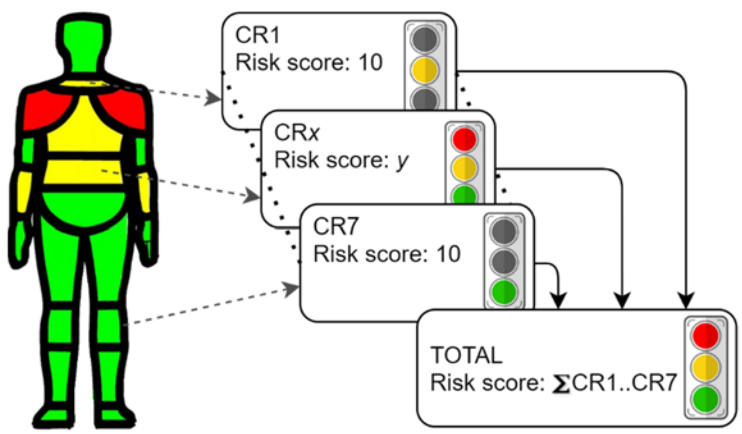

Figure 1. Visual representation of the ergonomics criteria in SERA. Each criterion assesses stresses on specific body parts and/or types of forces and loads. To maintain confidentiality, the mapping of body parts and the risk scores here are for demonstration purposes only.

There are various statistical methods and study designs which can be employed to epidemiologically validate methods for risk assessment. The arguably ideal design entails prospective longitudinal observations, allowing one to observe predicted and real outcomes. In a rare example of such a study for a specific assessment tool, the RNLE was validated by monitoring a cohort of 258 persons over a period of 4.5 years for the development of MSDs, demonstrating a hazard ratio of 4.3 for the associated peak lifting index (Garg et al., 2013). The reader can surmise the efforts (monetary, time, etc.) required to carry out such a thorough investigation. More commonly, cross-sectional and/or retrospective data are used. The newly released KIMs in Germany used such an approach to validate their results with approximately 1200 employees and 120 workplaces (Klussmann et al., 2017; MEGAPHYS, 2019, 2020). The EAWS was also investigated recently using a retrospective analysis of 292 automobile manufacturing workers, demonstrating significantly increased risk for MSDs with an increasing EAWS classification (Monaco et al., 2019). Finally, is it not uncommon for assessment methods to be developed and considered valid,

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based solely on an expert consensus and/or considering the vast underlying science demonstrating clear relationships between known risk factors and work-related MSDs. There are numerous ergonomics assessment methods which enjoy widespread acceptance and use despite a lack of the aforementioned formal validation studies (Takala et al., 2010). In summary, while longitudinal studies of assessment tools remain the gold standard, the required resources may not be justified, especially considering the accepted validity of the underlying risk factors and methods/standards. However, relying solely on the validity of underlying science, and forgoing formal statistical validation is both scientifically questionable and unwise with regard to the widespread acceptance of such tools.

A further limiting factor when carrying out the aforementioned studies, depending on the country in question, may be how certain types of health data are handled. In the country of interest, Germany, a country-wide socialized insurance, which all companies pay into proportionally to their size and risk classification, manages the entire process of investigation and classification of a potential work-related MSD, including managing any medical expenses, rehabilitation, lost wages, etc. (DGUV, 2017, 2020). This process results in a lack of transparency regarding potential work-related MSDs from the perspective of the employers, making it being near impossible to retroactively allocate specific workplace risk assessments to future health outcomes. Further, due to relatively strict European privacy laws ("Regulation (EU) 2016/679," 2016), and strong workers' councils, an internal tracking of such data would pose an inordinate burden on researchers. In the face of such difficulty, researchers and practitioners operating in these countries desire validation procedures requiring a justifiable effort, given that the discussed methods are typically already based on reproducible scientific data.

The purpose of this investigation is twofold; to propose a novel methodology for safety and ergonomics assessment tool validation and apply this methodology to the tool SERA. The underlying data sources for the proposed method still rely on risk assessments and actual health outcomes, however, this data is considered in aggregate, since, due to the reasons noted above, a one-to-one association of workplace assessments and associated health outcomes is not feasible. As discussed, the screening tool SERA was designed specifically based on scientifically established work-related MSD risk factors and a variety of existing ergonomics tools and standards. Therefore, it can be surmised that SERA already fulfills the criteria for construct validity. In determining which postural, force, and load stresses were relevant for inclusion in SERA, an organisation-wide survey was carried out and experts from relevant departments were consulted, suggesting a certain level of content validity. In applying the novel statistical approach developed here to the data, the criterion validity of SERA is investigated. Further, the results of the statistical approach help to elicit focus areas, a prioritization for future interventions, and derive threshold values for long-term monitoring. The steps required for the statistical procedure are outlined and generalized such that other practitioners may use them for their purposes.

2. Material and Methods

2.1 Independent variables

The SERA tool is used by the automobile manufacturer in question at all worldwide production facilities. Internal regulations require that all production workplaces are assessed using this tool. As mentioned earlier, SERA is used for both ergonomics, and risk analyses, although the further focus here will be solely on the ergonomics criteria. The ergonomics section of the tool is comprised of seven criteria (CR), of which each addresses a specific type of postural-, force-, or load-related stress. Within each criteria the relevant stresses are assessed using a combination of exposure (duration/frequency) and severity (intensity) data. The evaluation of a criterion results in a quantitative risk score and a traffic light color (where a red color represents a high risk). Similarly, for the overall cluster of seven ergonomics criteria, another risk score and traffic light are generated, resulting in a total of eight possible independent variables (CR1, CR2, CR3, CR4, CR5, CR6, CR7, and TOTAL) when considering the risk score and traffic light colors respectively. Collinearity between risk scores and traffic light colors should be limited, since traffic light colors are not strictly dependent on the risk score, i.e. a statistical analysis of both would not necessarily result in the same outcome.

For all five production facilities in Germany all the current analyses were exported, for a total of 26,525 workplace assessments. The risk scores and traffic light colors for all analyses were aggregated by the corresponding departments; arithmetic mean of the risk scores and the percentage of red traffic light colors. For the purposes of the further statistical analysis each variable was converted to a unit normal distribution.

2.2 Dependent variables

Despite the earlier discussed challenges regarding monitoring individual predicted and actual health outcomes in Germany, the manufacturer under study here internally manages an optional, employee-only health insurance. Clearly, due to

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privacy concerns, the individual data are not available, however an annual reporting of injury and illness types occurs on a departmental level using various metrics representing the prevalence of the injury and illness types. The focus of this investigation are the metrics for the category “musculoskeletal disorders” for the 2019 reporting year.

For the five production facilities in Germany the reports for all available departments were exported for a total of 58. These departments were then matched with the departments for which there were SERA analyses in the system, resulting in the exclusion of 5 departments (for example, departments involved exclusively in office work would not have SERA analyses). In total, these 53 departments have 34,618 employees of which 27,527 are represented in the data, since data are only gathered on those insured using the selective insurance, for a 79.5% coverage of the workforce. This coverage was deemed sufficient to continue with the analysis. Department sizes ranged from 41 to 4,888 employees with a mean of 653. Mean employee ages within the departments ranged from 35.8 to 53.7 years, with an overall mean of 45.2 years, weighted by department size. The percentage of female employees within the departments ranged from 2 to 33%, with an overall weighted mean of 8.6%. The actual outcome variables selected for further analysis were chosen specifically with the purpose of addressing the overall prevalence and severity of musculoskeletal disorders; number of incidents requiring time away from work per 100 insured years (INC/100), the total number of days away from work per 100 insured years (DAYS/100), and the percentage of employees for the department diagnosed with a musculoskeletal disorder for the reporting year (%MSD). These data were selected to reduce the possibility of collinearity and also represent varying dimensions of MSDs; incidence, severity, and prevalence respectively.

The final data processing step in preparation for the statistical analysis was to categorize the above-mentioned variables into “low” and “high” risk groups, based on percentiles. In this analysis, the 50th and 75th percentiles were used, i.e. the top 50 and 25%. Therefore, for each of the outcome variables (INC/100, DAYS/100, and %MSD) the department was classified binarily based on the distribution of all departments. The upper percentile (25th) was selected specifically to ensure a sufficient number of data points (minimum 10) in the “high” risk category, thereby avoiding insufficient degrees of freedom in the forthcoming statistical analyses. In total, the described procedure resulted in six dependent variables; three metrics on musculoskeletal disorders for each of the two percentiles. An overview of all variables is presented in Table 1.

Table 1. Overview of independent and dependent variables used in the analysis.

Independent variables		Dependent variables	
Mean risk score	Percentage of red traffic lights	Percentile	MSD metrics
CR1	CR1	50 (Top 50%)	INC/100
CR2	CR2		DAYS/100
CR3	CR3		%MSD
CR4	CR4	75 (Top 25%)	INC/100
CR5	CR5		DAYS/100
CR6	CR6		%MSD
CR7	CR7		
TOTAL	TOTAL		

2.2 Statistical analysis

Multiple logistic regressions were applied to each of the two groups of independent variables (mean risk score and percentage of red traffic light colors) for each of the six dependent variables, resulting in a total of 12 regressions. The logistic regression was chosen here as it is generally preferred when studying cross-sectional data for chronic illnesses (Thompson, Myers, & Kriebel, 1998). Studies discussed previously have also employed logistic regressions for similar data sets (Ghasemkhani et al., 2006; Piranveyseh et al., 2016). A further benefit of the logistic regressions are the model coefficients themselves, which can serve as threshold values for future monitoring. These threshold values are not reported here for reasons of confidentiality and since they are meaningless without a detailed understanding of the SERA system itself. Odds ratios were deemed applicable due to the low baseline prevalence of MSDs (Schmidt & Kohlmann, 2008; Zhang & Kai, 1998). The regressions were determined using a bidirectional stepwise procedure with α=0.15 for in- and exclusion. A stepwise procedure was chosen to help elicit the predominating explanatory variable(s). These α-values were selected to minimize model sizes, while maximizing the explained variability (R^2), and are in line with typical values (Bendel & Afifi, 1977). Significant odds ratios were concluded at p<0.05.

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Following the initial set of regressions (Round 1), the results were assessed to determine predominant variables or patterns. In order to elicit further explanatory variables, the predominant variable(s) from Round 1 were excluded, and another set of regression models were calculated (Round 2). Repeating the same grooming and iteration procedure a final time (Round 3) did not yield significant variables, and the analysis was therefore concluded.

This iterative and selective approach was borrowed from the machine leaning field, in which iterative modelling and targeted model grooming are used to elicit explanatory variables (Mitchell, 1997). All statistical analyses were performed using Minitab® 19 (State College, Pennsylvania, USA).

3. Results

The results of all regression models can be seen in Table 2. Notably, in the first set of regression models (Round 1) it can be observed that only the variable CR5 was significant, for 10 of the 12 models. For two models using the "percentage of red traffic lights" variables, no significant variables were identified. The mean odds ratio for the risk scores are 2.5 and 3.1 for the 50 and 75th percentile respectively. For the percentage of red traffic light colors, the mean odds ratios were 13.2 and 7.3 for the 50 and 75th percentile respectively.

Table 2. Results (R^2 and odds ratios) of all logistic regression models. Significant odds ratios (p<0.05) are highlighted in **bold**. Empty fields indicate that a given variable was not included in the model, based on the defined stepwise criteria. Fields with a "-" indicate that the variable was actively excluded from the variable pool (round 2 only).

Round	Percentile	MSD metrics	Mean risk score									Percentage of red traffic lights								
			R^2	CR1	CR2	CR3	CR4	CR5	CR6	CR7	TOTAL	R^2	CR1	CR2	CR3	CR4	CR5	CR6	CR7	TOTAL
1	50	INC/100	8.8					**2.3**				14.1					**13.7**			
		DAYS/100	10.6					**2.6**				19.7		6.2			9.2			
		%MSD	9.8					**2.5**				14.5					**12.7**			
	75	INC/100	29.9					**4.0**		0.3		33.5					**8.3**	2.1		
		DAYS/100	18.0					**2.6**		0.5		24.7					**6.3**	1.6		
		%MSD	19.6					**2.8**		0.5		28.4		5.7				2.0		
2	50	INC/100	9.7		**3.2**			-	0.5			8.5					-			**2.2**
		DAYS/100	10.9			0.5		-		0.6	**3.1**	14.3		**12.4**			-			
		%MSD	9.5				**2.4**	-				9.1					-			**2.2**
	75	INC/100	18.0				**2.6**	-		0.3		23.8		2.5			-	2.1		
		DAYS/100	16.2				**2.5**	-		0.4		14.3		**3.3**			-			
		%MSD	10.7		**2.9**	0.4		-				28.4		5.7			-	2.0		

Seeing that CR5 dominated the initial regression models, another set of 12 regression models were calculated, this time under exclusion of CR5, to determine which other explanatory variable(s) may have an effect. In the second set of regression models (Round 2) a total of three distinct significant variables were identified, CR2 in four models, CR4 in three models, and TOTAL in 3 models (Table 2). Odds ratios for the significant variables ranged from 2.2 to 12.4. Two models using the "percentage of red traffic lights" variables, did not indicate any significant variables.

4. Discussion

The purpose of this investigation was to validate an internally developed tool used to assess ergonomics at a manufacturing company in Germany. The tool SERA was developed using data from validated scientific sources and methods and has the goal of assessing the major ergonomic stresses experienced in modern production settings. Validation of such internally developed methods using longitudinal epidemiological studies may be prohibitively expensive, in terms of both

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money and time, but still is recommended to derive causal relationships between observed stresses and MSDs. Further, due to privacy rights, data with a direct 1:1 relationship to injuries, MSDs, etc. to specific evaluations or risk assessments may be unobtainable.

4.1 Statistical analysis

The restrictions noted above (among others) necessitated the development of a statistical methodology which allows practitioners faced with such restrictions to investigate both the validity of their methods and results, identify areas in which specific, targeted interventions may have the highest success rate, and derive threshold values for long-term monitoring. Borrowing from machine learning, an iterative approach was developed, in which repeated model grooming was used to elicit variables of interest (Mitchell, 1997). The results of the investigation demonstrated that indeed the SERA tool is likely to have criterion validity, although further investigations of causal associations are needed to make this precise determination. Specific risk criteria were shown to significantly increase the odds of developing MSDs. Going forward, these results enable the company to set priorities for future ergonomic interventions, and implement a monitoring strategy using the coefficient values (not reported here) determined as part of the logistic regression procedure.

Figure 2 indicates how the practitioner may identify relevant data and prepare that data for the subsequent statistical analysis. The source of ergonomics or hazard and risk assessments should be clear to most practitioners. Determining the appropriate source for outcome data, however, may be more challenging. It is important to seek out data which is (or can be) normalized to the size of relevant organisational entities, i.e. the rate of injuries or MSDs. A further important consideration in data selection is the ability for both data sources to be aggregated on the same organisational level. The most detailed organisational level possible should be selected in an effort to both maximize data points, while ensuring clear attribution of independent and dependent variables. Following the data aggregation, dependent variables are coded to represent risk categories. Using their in-depth understanding for the data, practitioners must take care to select risk category level to ensure sufficient data points in both groups for a valid statistical analysis. Finally, data is matched using the selected organisational entities. To reduce size effects, it is recommended to adjust the independent variables to a unit normal distribution.

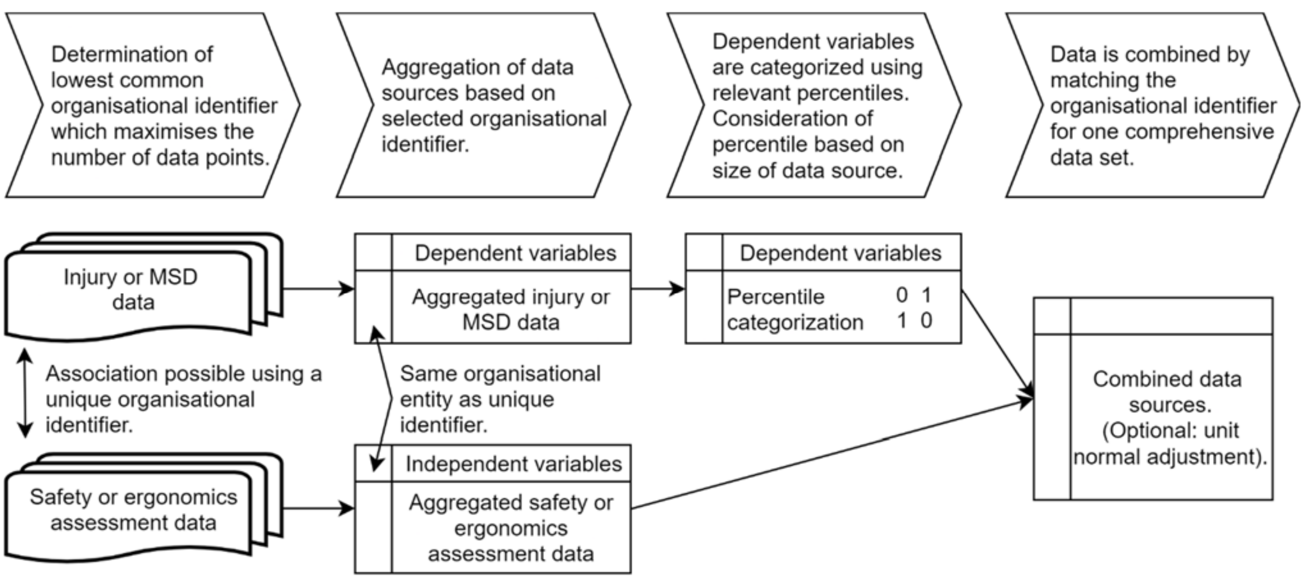

Figure 2. Process for data identification and preparation for statistical analysis.

Following the data aggregation, preparation, and matching noted above, multiple logistic regressions are used to determine significant variables (ergonomic or safety risk factors) leading to an increased likelihood of being categorized as high risk (see Figure 3). Based on the results of these logistic regressions, the variables may be groomed to exclude significant results and the logistic regressions repeated, in an attempt to elicit further explanatory variables. This process is repeated iteratively until the criteria for significance are no longer met. The exact parameters used for the logistic regressions (for

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example, the α for in-/exclusion, criteria for variable grooming, etc.) are likely to vary from those selected here, and the practitioner is encouraged to make use of their practical knowledge and experience with the data available to them.

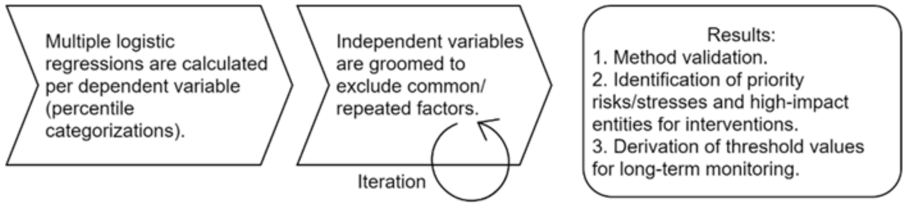

Figure 3. Process for iterative logistic regressions and variable grooming.

The results of the above-described methodology (assuming significant variables can be elicited) is a validation of the assessment method, identification and prioritisation of high-impact risks and stresses, and a set of threshold values for identifying and monitoring problematic organisational entities in the future (using the model coefficients). Although beyond the scope of this paper, practitioners may wish to take additional steps to further verify the plausibility of the statistical results, e.g. questionnaires, interviews, etc.

Regarding the proposed method there are two limitations worth noting. Firstly, there is the assumption of similarly structured data. This means not only do the data sources both have to be assignable by the same department levels, but those departments need to granular enough to create sufficient data points for statistical testing. With these conditions met, practitioners should also pay careful attention to the methods section here when preparing their data to ensure that variables are selected and prepared in such a way to minimize collinearity and order effects.

Secondly, it should be noted that this methodology is not designed to replace or be considered equal to a longitudinal, epidemiological validation of assessment tools. As highlighted by the authors throughout this text, there is a high degree of practitioner subjectivity involved in the data preparation, model parameter selection, and variable grooming procedures. This means both that the same method may not be adequate for superficially comparable data and different modelling choices will yield different results. In applying the methodology developed here, the practitioner must foremost consider the goal of the analysis (not in terms of predetermined outcomes, but rather the research questions) and make informed choices throughout the process to help answer the questions of interest.

In summary, the methodology proposed here can be applied by practitioners when working with similarly structured data in order to validate an ergonomics tool, determine priorities in terms of ergonomic stresses and high-impact organisational entities, and derive threshold values for monitoring stresses and hazards in the future.

4.1 Results Specific to SERA

In the case of the manufacturing company investigated here, the significant criteria elicited (CR5 in round 1 and CR2, CR4, and overall, in round 2) in the statistical analyses mirrored long-standing and known ergonomic stresses, and were elicited in the order of expected priorities.

As discussed earlier, the methodology developed here is a mixture of common validation approaches, using cross-sectional health outcome data, paired with risk identifiers. Despite the aggregate nature of the data, the resulting odds-ratios for the significant risk factors (2.3 to 4.0 for the risk score, and 2.2 to 13.7 for the percentage of red traffic lights) are within range of other investigations, using longitudinal observation (Werner, Franzblau, Gell, Ulin, & Armstrong, 2005) and retrospective analyses (Monaco et al., 2019). Further, it should be noted that different outcome variables used here had similar results, suggesting that the results were not by chance, thereby further supporting the validity of the results presented here and the SERA tool itself.

The investigation here is not without limitations. One major limitation is the possibility for confounding in the health outcome variables (insurance data). The insurance outcome variables here may include MSDs from sources other than employment, e.g. private, second job, etc. This effect cannot be minimized as the data gathered by the insurance company purposely has no information regarding the possible source of the MSDs (due to privacy), meaning that some of the MSDs included here may have resulted from personal factors. As discussed earlier though, the fact that results were replicated with multiple variables and mirrored known issues, suggest that any MSDs outside of employment are likely negligible. Practitioners using similar data should be aware of these effects and try to minimize them where possible.

Only about 80% of the workforce were included in the health outcome variables. This means, for example, that it is possible for employees with high ergonomic stress jobs resulting in MSDs not to be included in the health outcome data.

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However, socioeconomic factors in the country of interest (Germany) mean that production employees are more likely to take part in the internal insurance offered, than, for example, office workers, who are inherently at a lower risk for the ergonomic stresses captured using SERA and the resulting MSDs. There are two main reasons for this; when comparing the internal insurance to most other public insurance options, the internal insurance typical offers the best rates with the same or better conditions than any public options, and further, typically only those making substantially more money, such as white-collar workers, can afford alternate private insurance options. Taken together, this means that production employees are overall more likely to take advantage of the affordable internally offered insurance and more so than office workers. Further, while being far from ideal, an 80% workforce coverage should be considered respectable and representative.

Finally, it should be noted, that the ergonomic assessment data here were obtained by persons with varying expertise in ergonomics, meaning there is potential for inaccuracies. This likelihood, however, is reduced in the case of the company studied here, since employees which perform assessments require several days of training prior to receiving access authorization to the SERA tool. Further, regular audits and spot-checks both help ensure the accuracy of the data. Practitioners should be aware of this limitation in their own data and determine the extent to which their data source is reliable or requires possible validation prior to performing statistical analyses.

5. Conclusions

The purpose of this paper was to develop, describe, and apply a methodology when only aggregate safety and ergonomics, and health outcome data is available. Based on privacy regulations, practitioners may find themselves with valuable data, but no method for analysing this data to draw practical conclusions. The methodology proposed here borrows from traditional epidemiological analysis and machine learning, applying an iterative modelling approach. Results of this method may include; a validation of the underlying assessment tool, a prioritization of countermeasure and intervention targets, and the derivation of threshold values for long-term monitoring. In applying this methodology to the data for a large manufacturing company, the authors were able to determine ergonomics stresses resulting in significant odds ratios for MSDs for four assessment criteria, which aligned closely with known issues at the company. Practitioners may use the proposed method for their own companies, in cases where the data are structured similarly.

6. References

Arghami, S., Kalantari, R., Ahmadi Kionani, E., Zanjirani Farahani, A., & Kamrani, M. (2016). Assessing Prevalence of Musculoskeletal Disorders in Women Workers in an Automobile Manufacturing Assembly Line. *Journal of Human Environment and Health Promotion, 1*(2), 75-79.

Bendel, R. B., & Afifi, A. A. (1977). Comparison of stopping rules in forward "stepwise" regression. *Journal of the American Statistical Association, 72*(357), 46-53.

DGUV. (2017, 16.01.2017). Die Berufskrankheit - was ist das? Retrieved from https://www.dguv.de/webcode.jsp?query=d1068085

DGUV. (2020, 07.07.2020). Meldung des Verdachts einer Berufskrankheit. Retrieved from https://www.dguv.de/webcode.jsp?query=d678324

Garg, A., Boda, S., Hegmann, K. T., Moore, J. S., Kapellusch, J. M., Bhoyar, P., Bloswick, D. (2013). The NIOSH Lifting Equation and Low-Back Pain, Part 1 Association With Low-Back Pain in the Backworks Prospective Cohort Study. *Human Factors: The Journal of the Human Factors and Ergonomics Society*.

Ghasemkhani, M., Aten, S., & Azam, K. (2006). Musculoskeletal Symptoms Among Automobile Assembly Line Workers. *Journal of Applied Sciences, 6*(1), 35-39.

Hussain, T. (2004). Musculoskeletal symptoms among truck assembly workers. *Occupational Medicine, 54*(8), 506-512.

Klussmann, A., Liebers, F., Brandstädt, F., Schust, M., Serafin, P., Schäfer, A., Steinberg, U. (2017). Validation of newly developed and redesigned key indicator methods for assessment of different working conditions with physical workloads based on mixed-methods design: a study protocol. *BMJ Open, 7*(8), e015412. doi:10.1136/bmjopen-2016-015412

Liberty Mutual Workplace Safety Index. (2019). Retrieved from https://business.libertymutualgroup.com/business-insurance/Documents/Services/DS200.pdf

MEGAPHYS. (2019). *MEGAPHYS - Mehrstufige Gefährdungsanalyse physischer Belastungen am Arbeitsplatz, Vol. 1* (F 2333). Retrieved from Dortmund: https://www.baua.de/DE/Angebote/Publikationen/Berichte/F2333.pdf?__blob=publicationFile&v=11

DOI: https://doi.org/10.37266/ISER.2022v10i1.pp1-9

MEGAPHYS. (2020). *MEGAPHYS - Mehrstufige Gefährdungsanalyse physischer Belastungen am Arbeitsplatz, Vol 2.* (3/2020). Retrieved from Berlin: https://publikationen.dguv.de/widgets/pdf/download/article/3635
Mitchell, T. (1997). *Machine Learning* (1 ed.). New York: McGraw-Hill.
Monaco, M. G. L., Uccello, R., Muoio, M., Greco, A., Spada, S., Coggiola, M., Miraglia, N. (2019). Work-related upper limb disorders and risk assessment among automobile manufacturing workers: A retrospective cohort analysis. *Work-a Journal of Prevention Assessment & Rehabilitation, 64*, 755-761. doi:10.3233/WOR-193037
Piranveyseh, P., Motamedzade, M., Osatuke, K., Mohammadfam, I., Moghimbeigi, A., Soltanzadeh, A., & Mohammadi, H. (2016). Association between psychosocial, organizational and personal factors and prevalence of musculoskeletal disorders in office workers. *International Journal of Occupational Safety and Ergonomics, 22*(2), 267-273. doi:10.1080/10803548.2015.1135568
Regulation (EU) 2016/679. (2016, 27.04.2016). Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32016R0679&from=EN
Schmidt, C. O., & Kohlmann, T. (2008). When to use the odds ratio or the relative risk? *International journal of public health, 53*(3), 165.
Takala, E.-P., Pehkonen, I., Forsman, M., Hansson, G.-Å., Mathiassen, S. E., Neumann, W. P., Winkel, J. (2010). Systematic evaluation of observational methods assessing biomechanical exposures at work. *Scandinavian journal of work, environment & health*, 3-24.
Thompson, M. L., Myers, J., & Kriebel, D. (1998). Prevalence odds ratio or prevalence ratio in the analysis of cross sectional data: what is to be done? *Occupational and Environmental Medicine, 55*(4), 272-277.
Vos, T., Lim, S. S., Abbafati, C., Abbas, K. M., Abbasi, M., Abbasifard, M., Abdelalim, A. (2020). Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet, 396*(10258), 1204-1222.
Werner, R. A., Franzblau, A., Gell, N., Ulin, S. S., & Armstrong, T. J. (2005). Predictors of upper extremity discomfort: a longitudinal study of industrial and clerical workers. *Journal of Occupational Rehabilitation, 15*(1), 27-35.
Zhang, J., & Kai, F. Y. (1998). What's the relative risk?: A method of correcting the odds ratio in cohort studies of common outcomes. *JAMA, 280*(19), 1690-1691.

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