Introduction

America’s workforce is becoming more diverse. Generally, this diversity includes workers with different anthropometry (size, shape), capabilities, work experiences, and ethnicities. More importantly, the workforce is also aging and becoming heavier. However, the impact of aging and obesity is typically not considered in traditional ergonomic modeling. This paper explores the potential impact of these factors and proposes several ways to factor these characteristics into ergonomic models. Research is underway to quantify and empirically test new methods for evaluating work place risk. This paper details the application of an age modifier to the Revised NIOSH Lifting Equation (RNLE) (Waters, Putz-Anderson, and Garg, 1994) and proposes how such methods could be expanded to obesity and other worker personal characteristics. The RNLE is perhaps the most widely used manual material handling (MMH) evaluation method in use. Effective modifications to the RNLE have been demonstrated. For example, Sesek et al. (2003) modified the RNLE to allow analysis of one-handed lifting tasks. The predictive ability of the tool was maintained, but the number of jobs capable of RNLE analysis greatly increased. Modifying the RNLE to account for age will not increase the number of jobs capable of being analyzed, but rather has the potential to improve the predictive ability of this tool when dealing with older and presumably more at risk populations.

Methods

Data for this investigation were gathered from two previous studies:

1. An automotive manufacturing ergonomic field study.
2. A morphometric study of low back geometry using MRI technology.
Automotive Study

Data were analyzed from a database consisting of 667 manufacturing jobs from a previous automotive study. The database included historical injury data for the analyzed jobs as well as symptom interviews for 1,022 participants (Sesek, 1999). A subset of 113 subjects with manual material handling tasks appropriate for applying the RNLE was selected for the current study. The subjects ranged in height from 59-77 (69.8 ± 3.6), weighed between 115-350 pounds (192.5 ± 45.7), and were 22-65 years of age (41.4 ± 11.2). There were 92 male and 21 female subjects. Researchers had no personal information regarding participants beyond height, gender, and self-reported level of discomfort. All data were analyzed in aggregate. The original data were collected at six different automotive plants. Only jobs with well-defined lifting activities were included (administrative jobs or jobs that did not have well defined tasks were not analyzed). Subject data used for this study include height, weight, age and gender (used to estimate the lower lumbar spinal geometry) and subject reports of discomfort assessed by ratings of perceived discomfort. In the original study, the RNLE Cumulative Lifting Index (CLI) was used to predict jobs with injuries. CLIs ranged from 0.3-5.0 (1.7 ± 1.0). Negative health outcomes were defined as self-reported low back pain (LBP) and LBP-related medical visits reported for the subject’s job. Cases included subjects with reported low back pain working on jobs that had at least one reported injury in the previous year. Controls included subjects with no low back pain working on jobs that had not had a reported injury in the previous year. The prevalence of low back pain for this population was 0.16.

MRI Study

Regression models were used to estimate individual spinal geometry, calculating the cross-sectional area (CSA) of the L5/S1 intervertebral disc (IVD) with subject height and gender. These regression models were developed using geometric measurements on MRI scans and subject anthropometric characteristics (Tang et al, 2014). MRI scans were performed using a 70cm Open Bore 3T scanner (MAGNETOM Verio, Siemens AG, Erlangen, Germany) at the Auburn University MRI Research Center (Figure 1). MRI scans were analyzed using OsiriX© software (version 4.1.1, 32-bit, Pixmeo, Geneva, Switzerland) (Figure 2).
IVD cross-sectional areas (CSAs) can be estimated using the regression relationship developed in the previous MRI study (Tang, et al, 2014). This relationship is shown in Equation 1.

$$\text{L5/S1 IVD CSA} = -2.629 + 0.070 \times HT + 0.264 \times G,$$

$HT = \text{stature in inches and } G = 0 \text{ for females and } 1 \text{ for males}$

Equation 1: regression relationship of height (HT) and gender (G) to IVD cross-sectional area.

**Experimental Design**

For each subject, a CLI was calculated as in the original automotive study. A decision cut point of 3.0 was used to predict “risky” jobs. Alternative CLIs were computed by creating additional multipliers for the RNLE. The RNLE has six multipliers and a load constant (LC) of 51 pounds. The multipliers include a horizontal multiplier (HM), vertical multiplier (VM), distance multiplier (DM), asymmetry multiplier (AM), frequency multiplier (FM), and a coupling multiplier (CM). New multipliers included gender, age, body mass index, and IVD CSA multipliers. Equation 2 below shows the original RNLE multipliers used to compute a recommended weight limit (RWL).

$$\text{RWL} = \text{LC} \times \text{HM} \times \text{VM} \times \text{DM} \times \text{AM} \times \text{FM} \times \text{CM}$$

Equation 2: Revised NIOSH Lifting Equation

The actual weight lifted is divided by the computed recommended weight limit to create the lifting index (LI). When the LI is $\geq 3.0$, the lift is considered to pose risk for
“nearly all workers” according to NIOSH (Waters, et al, 1994). Equation 3 below shows the LI.

\[
\text{LI} = \frac{\text{Actual Weight}}{\text{RWL}}
\]

Equation 3: Lifting Index

The cumulative lifting index or CLI is analogous to the LI, but considers jobs with multiple lifting tasks of varying weights and/or parameters. The CLI is a single metric intended to estimate the risk of the entire job.

**Proposed Multipliers**

Several novel multipliers that describe intrinsic characteristics of the subject were selected for evaluation. These included gender, body mass index (BMI), age, and an approximation of the low back intervertebral disc (IVD) size as a scaling factor to adjust risk based on a subject’s specific anthropometry. Previous work by the authors (Sesek, Tang, Güngör, Gallagher, and Davis, 2014) demonstrated that area could be used to convert force to stress (force per unit area), thereby improving the predictive ability of ergonomic surveillance tools driven by back compressive force (BCF).

A gender multiplier (GM) of 2/3 for female subjects as discussed in the RNLE (Waters et al., 1994). A body mass index (BMI) multiplier (BMIM) was applied to penalize BMI in excess of 30. The BMI multiplier consisted of \( \frac{30}{\text{BMI}} \) for BMIs > 30 and 1.0 for BMIs under 30. An age multiplier (AGEM) to account for strength losses expected from aging was also tested. The age multiplier was 1.0 for subjects under the age of 40 and decreased by 1% for each year of age beyond 40. The IVD CSA multiplier (IVDM) was computed by normalizing against the area of 50th percentile male IVD at the L5/S1 segment of the low back. This multiplier was computed as subject IVD divided by the reference IVD (50th percentile male). All new multipliers were tested individually and in groups to see if predictions could be improved for the RNLE CLI.

The proposed multipliers can be simply added to the RWL calculation as shown below in Equation 4.

\[
\text{RWL} = \text{LC x HM x VM x DM x AM x FM x CM x GM x BMIM x AGEM x IVDM}
\]

Equation 4: Revised NIOSH Lifting Equation with Proposed Multipliers

However, since these factors are intrinsic to the subject, they do not have to be computed task-by-task at the RWL level and can be used to modify the CLI directly. One simply computes the CLI as per NIOSH guidelines and then modifies the output as shown in Equation 5 below.

\[
\text{CLI}_{\text{mod}} = \text{CLI} / (\text{GM x BMIM x AGEM x IVDM})
\]

Equation 5: Modification of CLI Based on Personal Characteristics

Modifications to the RNLE were proposed to account for an increasingly diverse, aging, and obese population of workers. For example, a given job may present more risk to an elderly and obese worker than a young and fit worker. Direct comparisons are made
between the predictions of the unmodified CLI and the proposed CLI modifications.

**Results**

Table 1 compares the performance of the original RNLE to the RNLE as modified by proposed personal characteristic modifiers. Note that age and BMI do not improve the model’s predictive ability by themselves. CLIs for individual jobs changed, but overall model performance did not improve.

<table>
<thead>
<tr>
<th></th>
<th>RNL +AGE</th>
<th>+BMI</th>
<th>+G</th>
<th>+IVD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Odds</td>
<td>6.3</td>
<td>6.3</td>
<td>8.0</td>
<td>9.0</td>
</tr>
<tr>
<td>(95% CI)</td>
<td>(1.8-21.9)</td>
<td>(1.8-21.9)</td>
<td>(2.4-27.1)</td>
<td>(2.4-34.1)</td>
</tr>
<tr>
<td>Prevalence</td>
<td>0.16</td>
<td>0.16</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
<td>0.39</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>Positive Pred. Value (PPV)</td>
<td>0.46</td>
<td>0.46</td>
<td>0.46</td>
<td>0.50</td>
</tr>
<tr>
<td>Negative Pred. Value (NPV)</td>
<td>0.88</td>
<td>0.88</td>
<td>0.88</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Gender and IVD area modifications improved overall model performance: boosting sensitivity and positive predictive value for the gender multiplier (GM) and specificity and positive predictive value for the IVD multiplier (IVDM). Multiple modifiers combinations were also tested. Table 2 shows model performance when considering combinations.

<table>
<thead>
<tr>
<th></th>
<th>RNL +AGE +GM</th>
<th>+AGEM +IVDM</th>
<th>+AGEM +IVDM +BMIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Odds</td>
<td>6.3</td>
<td>9.44</td>
<td>6.8</td>
</tr>
<tr>
<td>(95% CI)</td>
<td>(1.8-21.9)</td>
<td>(2.7-33.2)</td>
<td>(2.2-21.2)</td>
</tr>
<tr>
<td>Prevalence</td>
<td>0.16</td>
<td>0.16</td>
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<tr>
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<tr>
<td>--------------------------------------</td>
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<td>------</td>
</tr>
<tr>
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<td>0.89</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Note that performance improves over the RNLE alone, but only the combination of AGEM and IVDM outperformed the single multipliers of GM (odds ratio 8.0) and IVDM (odds ratio 9.0). In fact, a model with all multipliers actually performed slightly worse than the RNLE alone (odds ratio of 6.1, 2.0-18.8). Since some of the new multipliers are correlated, the model may be “over corrected” for such factors. For example, women tend have smaller IVD areas than men (both based on gender and height differences) with both values tending to predict greater risk for smaller women.

**Discussion**

Modification of ergonomic surveillance tools using personal characteristics to improve model performance is feasible. Accounting for personal characteristics, particularly for persons who differ significantly from the average, can help progress the field of ergonomics. This concept can be applied to other tools and methods. The authors have also had some success using IVD area to convert back compressive force (BCF) to back compressive stress (BCS) (Sesek, et al, 2014). While predictive abilities improved, the shifts were not dramatic. Some limitations were present in this study and this concept should be explored further with additional data sets in prospective cohort studies.

**Limitations**

There are several limitations associated with this pilot study that should be addressed as this concept is explored further. These limitations can be summarized as follows:

1. Assumptions regarding personal characteristics: It was assumed that stress capabilities are consistent across individuals. There may be differences based on the interaction of age, gender, previous injuries, and other personal factors not considered in this research. These should be explored in subsequent research.
2. Overly simplistic assessment of risk in the referenced ergonomic study: individual subject discomfort was included in the definition of a negative health outcome (case), but injury status was determined for the job as whole, not for the specific individual. Subsequent studies should use a more clear case/control methodology. Ideally, individuals would be followed prospectively.

Despite the limitations described above, the modified tool performed well and it is anticipated that these concepts can easily be incorporated into new or existing models by simply considering the subject’s basic anthropometry (height, weight, age, and gender in this study). There is also the possibility that the risk estimation of other ergonomic tools can be enhanced. For example, expected decrements in strength related to age can also be
used to modify upper extremity tools.

**Conclusion**

Based on the findings of this pilot study, the following conclusions are drawn:

1. Personal characteristic multipliers show promise as a means of improving risk assessments, particularly for relatively large and small subjects and should be explored further.
2. The concept of “scaling” risk based on subject size and modifying ergonomic survey tool outputs with this data should be explored further.
3. Accounting for personal characteristics can help improve ergonomic modeling. Other factors that could be considered include body composition (rather than crude BMI), previous injury history, and physical condition.

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**Bibliography**


