REPORT NO. 498

Wearable Technologies for Safety

Results of research carried out as MRIWA Project M498

at Soter Analytics

by

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1. Introduction

Research undertaken internally at a mature mining company (operating in the Pilbara for 50+ years) showed that MSK injuries are the costliest injury type for a workforce, costing more than all other injury types combined. The average compensation cost per employee (regardless if the employee is injured or not) is $2,100 per year. Safe Work Australia estimate that compensation costs are only 25% of the total cost of an injury, with the other 75% including lost productivity, meaning that the average cost is actually $8,200. For a 5,000-person workforce, this cost is $41M.

This R&D project used wearable sensors to collect raw movement data from workers in the resource industry in Western Australia, specifically Roy Hill. This data was analysed, with algorithms developed to predict if a worker is at an increased risk of experiencing an injury (and in particular, a MSK injury). If the risk is high, a notification will be communicated to the worker, allowing them to make changes that can prevent the injury from occurring.

The 2 key R&D steps were as follows:

- Develop algorithms that analysed the raw data captured by wearable sensors. The purpose of these algorithms was to identify at-risk movements and activities as events, measure a number of characteristics of these events, and quantify the risk of each event.
- Develop an actionable insights process that can both warn a worker immediately if they are at an increased risk of injury, and to enable an organization to analyse the risk profile of the entire workforce

Development for this project is took approximately 5 months. As part of our relationship with Roy Hill, we undertook two trials. The first trial in July 2017 was to collect data to develop the algorithms and reporting process and prove the value of this project. The second trial was in November-December 2017 and tested the accuracy of the developed algorithms and the user reaction to the actionable insights feedback.

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2. Methodology

2.1 Risk Model

A risk model was developed to translate how certain at-risk movements will result in musculoskeletal (MSK) injury risk. This allowed each at-risk MSK movement to be quantified and thus the overall risk of injury to the worker could be calculated. This includes the inter-dependency of events that can potentially significantly increase the individual event risk.

2.2 Wearable Device Location

A wearable device was developed to capture data from the worker that could then be analysed for MSK risk. The location of the device/s is important as it must be in a suitable location in order to be able to make the right measurements.

The ideal location of the device was done through the following steps:

1. Literature review of what caused MSK risk.
2. Characterisation and grouping of events and measuring the importance of each group.
3. Identification of ideal device location to measure each group of movements.
4. Identification of suitable sensor modules to measure each group of movements.
5. Development of prototype sensor to test effectiveness.
6. In-field testing with workers and visual observation of tasks.
7. Review of data and visual observations, and MVP level algorithms developed.
8. Final in-field test and observations to prove algorithms are accurate in measuring MSK risk.

The goal of choosing the suitable location of a device was to determine the appropriate trade-off between percentage of MSK at-risk movements that can be identified and the practicality of the wearable device for both the environment of working locations and the usability for the worker.

2.3 Event Detection Algorithm

A worker may be working for 8-12 hour shifts but only a small fraction of this is spent putting their MSK system at risk. Algorithms needed to be developed to determine when these at-risk moments were occurring, to allow the characteristics of these movements to be recorded and then quantified.

The majority of MSK risk comes from orientation of the body, usually when the body approaches the maximum end-point movements. Data collected from the device (that was recorded as our event detection algorithm had detected it as an at-risk movement) was processed to determine the orientation of the MSK system during this event.

The second largest contributor (after orientation) of MSK risk comes from the intensity of a movement. This particularly becomes relevant when a high-risk orientation is combined with a high intensity or force on the MSK system.

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Typical analysis of intensity is done through measuring the weight of the object that the worker is handling. This largely ignores the strength and fitness of the worker, how fatigued they are, and how accustomed their body is to making particular movements. We identified an opportunity to instead measure the intensity on the MSK system which then accounts for these differencing factors.

The development of the algorithms had the following steps:

1. Recording of data with participants (volunteers, not our customer's workforce) who undertook a series of movements while being visually monitored and recorded.
2. Development of algorithms that determine and quantify different characteristics of at-risk movements
3. Testing with participants who again undertook a series of movements while being visually monitored and recorded.
4. Testing in-field to confirm accuracy.

2.4 Actionable Insights Process

Once the risk of MSK injuries could be quantified and thus predicted, this information needed to be presented to the right stakeholders within an organisation to allow for the risk to be mitigated and injuries to be reduced.

The two main personas of people using and acting on this data are the worker and the organisation's health and safety manager. Engagement is key for the worker, to ensure that they are wearing the device and interacting with the solution. The manager needs to see overall risk trends so that tasks, tooling and job locations can be redesigned to eliminate risk on a macro level.

Workers were surveyed to determine how engaging they found the actionable insights process while health and safety managers were interviewed at length to ensure they had the right data available to make the right decisions.

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3. Results

3.1 Risk Model

When creating the risk model, we took into account such factors as twisting, bending, duration of being in the static posture, frequency (lifts per minute), duration of working time without rest, and time spent resting. To define the units for the bending and twisting movement and creating risk score first literature analyses was performed.

3.1.1 Literature Review

The spinal muscles provide significant stability to the spine as shown by both in vitro experiments and mathematical models. Concerning the role of neuromuscular control system, increased body sway has been found in patients with low back pain, indicating a less efficient muscle control system with decreased ability to provide the needed spinal stability. (1).

Most likely the decrease in the neutral zone is responsible for pain reduction. A hypothesis relating the neutral zone to pain has been presented by some authors. The neutral zone is a region of intervertebral motion around the neutral posture where little resistance is offered by the passive spinal column. Several studies--in vitro cadaveric, in vivo animal, and mathematical simulations--have shown that the neutral zone is a parameter that correlates well with other parameters indicative of instability of the spinal system. It has been found to increase with injury, and possibly with degeneration, to decrease with muscle force increase across the spanned level, and also to decrease with instrumented spinal fixation. In most of these studies, the change in the neutral zone was found to be more sensitive than the change in the corresponding range of motion.

The neutral zone appears to be a clinically important measure of spinal stability function. It may increase with injury to the spinal column or with weakness of the muscles, which in turn may result in spinal instability or a low-back problem. It may decrease, and may be brought within the physiological limits, by osteophyte formation, surgical fixation/fusion, and muscle strengthening. The spinal stabilizing system adjusts so that the neutral zone remains within certain physiological thresholds to avoid clinical instability (2).

Lifting or carrying loads, whole-body vibration, and frequent bending and twisting proved to be the physical load risk factors consistently associated with work-related back disorders (3).

An increased risk of low back injury may result from flexion-induced disturbances to trunk behaviours. Such effects, however, appear to depend on the type of flexion exposure, and have implications for the design of work involving trunk flexion (4).

Trunk flexion exposures, whether prolonged or cyclic, result in viscoelastic deformation of passive tissues in the posterior trunk and consequently a reduction in trunk stiffness. A decrease in passive trunk stiffness can be compensated by extra activation of muscles, which may cause additional loads on joints and other soft tissues. Moreover, extra activation of muscles may increase metabolic cost and consequently contribute to muscle fatigue. The risk of low back disorders (LBDs) may be associated with excessive spinal loads and muscle fatigue.

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Initial moment, moment drop, and changes in normalized neutral zone increase exponentially with flexion angle. Bending starts to have influence on low back when bending angle exceed 30 degrees. That's why bending angle 30 was taken as a first point.

Faster extension movement creates a larger window during which the spine is exposed to instability and injury because of lack of muscle forces (5).

Heavy lifting or high force exertion of back muscles immediately after prolonged flexion could be a risk factor for low back disorders when the muscles lose their force generating capacity due to passive stretching.

A 30-s rest break in the middle of the flexion moderated viscoelastic responses of the tissue. Sufficient rest between consecutive full flexion tasks is important in reducing the risk of low back disorders. (5).

Initial moment, moment drop, and changes in normalized neutral zone increased exponentially with flexion angle. Flexion-induced changes in viscous properties and neutral zone imply an increase in internal loads and perhaps increased risk of low back disorders. NIOSH released the results of a study which found a correlation between the number lifts per shift and lower back pain. The study involved the self-reporting of multiple factors from a group of 138 manufacturing workers. The study found that lower back pain had the highest correlation (among the factors examined) to lifts per shift and to maximum lifting frequency. Repeated lifts every day at work will cause micro trauma, micro tears in the muscle fibres and related tissues which can eventually contribute to a weakening of the MSK support system. Because pain due to micro trauma increases very slowly over time, workers may ignore and dismiss it until something major happens but would definitely notice an overall increase in lower back pain (NIOSH,VIT).

Lifting loads over 25 kg and lifting at a frequency of over 25 lifts/day will increase the annual incidence of LBP by 4.32% and 3.50%, respectively, compared to the incidence of not being exposed to lifting. Intensity and frequency of lifting significantly predict the occurrence of LBP (7).

Structural abnormalities multilevel disc degeneration has been shown to exhibit higher presence and severity of low back pain than patients with skipped-level disc degeneration (i.e., healthy discs located in between degenerated discs).

3.1.2 Risk Model

Risk was calculated according to the formula from a number of coefficients:

Event Risk = Movement risk coefficient * awkward static posture risk coefficient * intensity risk coefficient * frequency risk coefficient * lack of rest risk coefficient; where movement risk is a combination of bending and twisting angle. The total risk score for a worker is cumulative of the event risk scores and can be decreased only through rest breaks of at least 5 minutes.

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Individual’s risk score = sum (Event Risk) * Rest coefficient

The coefficients of the bend and twist risk for each event are as follows:

	Twist Angle						
Bend Angle	**0**	**15**	**30**	**45**	**60**	**75**	**90**
30	1.09	1.80	2.90	4.39	6.27	8.54	11.20
45	1.65	2.36	3.46	4.95	6.83	9.10	11.76
60	2.50	3.21	4.31	5.80	7.68	9.95	12.61
75	3.77	4.48	5.58	7.07	8.95	11.22	13.88
90	5.69	6.40	7.50	8.99	10.87	13.14	15.80
105	8.59	9.30	10.40	11.89	13.77	16.04	18.70

For the quantification of the static posture risk, static posture coefficient was developed:

Length of Awkward Static Posture (seconds)	Awkward Static Posture Coefficient
10	1.45
20	1.55
30	1.65
40	1.75
50	1.85
60	1.95

Intensity is the force that is applied on the MSK system during a movement and was quantified from the following table:

Intensity of Movement	Intensity Coefficient
Low	1
Medium	2
High	4

Frequency is the amount of movements made in a short duration of time. High frequent movement fatigue the MSK system, increasing the risk of injury:

Movements/minute	Frequency Coefficient
<= 2	1
3	1.05
4	1.12
5	1.2
6	1.28
7	1.36
8	1.44
9	1.51
10	1.58
11	1.65
12	1.73
13	1.81

14	1.89
>= 15	1.97

Rest, which moderates the viscoelastic response of the muscle tissue, is defined as at least 5 minutes of time without any at-risk MSK movements. The following coefficients are applied:

Number of Hours Without Rest	Lack of Rest Coefficient
0	1
1	1.05
2	1.12
3	1.2
4	1.33
5	1.48
6	1.7
7	1.85
8	1.99

Finally, the overall risk score can be decreased by having rest breaks, allowing the MSK system to recover. The coefficient of these are applied to the cumulative risk score of a worker.

Rest Duration (min)	Rest Coefficient
5	0.93
10	0.85
15	0.78
20	0.73
30	0.68
45	0.61
60	0.54

3.2 Wearable Device Location

Literature review of past research and past experience within the team showed that there were a number of orientation characteristics that should be recorded:

- Bending angle of the back
- Twisting angle of the back
- Time spent in an awkward static posture with the back bent or twisted.
- Shoulder movements
- Elbow and wrist movements

3.2.1 Literature Review

Two studies were used to quantify the risk of injury of each location:

- 2012 Health Survey - National Center for Health Statistics
- 2013-2015 UK THOR-GP Survey

Both studies, combined with our customer data, showed that lower back/lumbar injuries were both the most common and most expensive. Next was shoulder injuries followed in third place by wrist injuries.

3.2.2 Identification and testing of potential device locations

Three potential locations were identified as possible locations for the device/s:

- Chest area
- Wrist
- Upper back

Testing occurred with all sensors on all three locations and simple MVP algorithms were written to determine if movements could be accurately measured – which were then rated out of 10. Workers were also surveyed to see how they found the different locations:

Device Location	Algorithm Score	Worker Score
Chest	8	9
Wrist	4	5
Upper back	9	9

134 workers were surveyed over a 4-week period

While the wrist was a suitable location to help measure wrist and shoulder risk, it was decided the device should be on the torso to measure the risk to the back. A decision was to have a single sensor, as it is easier for the worker to manage. This ruled out combining a wrist and chest or back device. There was a slight decrease in accuracy if the device was placed on the chest rather than the back but the decision was made to choose the chest as it is easier for the worker to manage and interact with the device.

3.3 Algorithm Development

Algorithms were developed to identify and then measure at-risk movements. These focussed on the movement and forces applied to the back. There were 5 research tasks undertaken to build and improve the algorithm accuracy. Individual progress on each task can be seen below. Overall accuracy of our algorithms is >95% accuracy for posture/movement detection, and 80% accuracy for intensity detection accuracy. The intensity accuracy is particularly interesting, explained below.

The following options were investigated to increase our accuracy:

a. [Improved recognition of different movements] Full reconstruction of coordinates over the movements with additional drift correction, it brings the ability to understand relative sensor position over the time.

This was successful and complete. The sensor now understands how it is attached to the shirt of the worker. This allows the worker to put the sensor in any orientation, so long as it is clipped tightly to the shirt.

b. [Improved recognition for different users] Use Dynamic Time Warping (DTW) to measure similarity between different time series data that display pattern but at different speeds.

Decided not to use. Instead, split movements into multiple sub-movements which could then be detected without having issues with different window sizes.

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c. [Noise movements, i.e. those we don't want to track] Use multiple specialized models; each of them can detect just one type of movements. In most cases it helps to raise overall accuracy dramatically.
Created a real time iterative model which give the ability to process the data immediately and detect upper body movements without storing the data and processing post-event. This model is largely what gives us the 95% posture/movement detection accuracy.

d. [Imperfect movement windows detection] Train models on imperfect data, i.e. change originally recorded data in a way it mimics errors in window detection and train classification model on larger train set of data, which is close to input data in real case.
This is what analyses the movements to determine forces on the body. Complete.

e. Intensity detection algorithm
Began with the idea to determine the weight of objects that workers were using, using an unsupervised machine learning technique called clustering. What was found in the data was that correlations between weights are different for different people due to varying strengths of individuals. Have also tested a neural network, however the accuracy of this model currently only sits at 60% accuracy

What we ended up creating is more of a force or intensity impact detection model. Instead of detecting weight, it detects the intensity of the force on the person. The physiotherapist on our team helped validate our model using EMS research which detects the stress on muscles while people were making movements that are detected by our solution. In addition, it's able to see how people fatigue and how the impact of lifting the same object increases over time.

3.4 Actionable Insights

The device and app communicate with the worker to explain to them their current MSK risk level and coach them on improving their techniques. In addition, the data is also communicated to the organisation to allow them to make changes to job and workplace design.

To communicate, a light was installed on device which changes colour as the day progresses to communicate the risk. Soter Analytics also have developed the android version of the app which breaks down the causes of risk and provides tutorials and personalized coaching. This app is now available on the Google Play store and the iOS version will be available in Q2 2018.

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