Using Sensors to Augment Safety

Research Report

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1. Executive Summary

1.1 Background and Aims

RESEARCH investigating the ever-increasing developments in wearable biological monitoring technologies supports a growing ecosystem of smart wearables that proactively identify and control workplace hazards. Offering individualised monitoring of fatigue, heat, vital signs, and workplace conditions, they provide information to supplement an individual's own perception of risk to achieve peak productivity outcomes, while keeping everyone safe. However, the value of these technologies has not yet been explored within water utilities, within an emerging literature of use cases across industry in general.

> The aims of this project were to trial a combination of well-established and novel sensing technologies in order to investigate their potential to enhance the safety of workers on site and on the roads. The project involved synthesising data from sensors, observations, and interviews, and monitoring workers during safety-critical tasks.

1.2 Methods

Interviews were conducted with n=21 employees from three sites (2 metropolitan, 1 regional). Areas for data collection were identified through the interviews. Participants identified fatigue, heat, and stress, and their interactions, as key hazards. Regional workers highlighted pipe repairs, particularly asbestos pipe removal, and meter reading as focus areas for wearable measurement. Metropolitan workers highlighted water testing and overnight shifts.

Wrist sensors (Geneactiv, ActivInsights, UK) were used to monitor patterns in sleep and activity levels (16 participants, 1-4 weeks each, 224 wear-days). Biometric smart shirts (Hexoskin Shirt, Carré Technologies Inc., Canada) were used to monitor heart rate and exertion (four participants, 1-2 36-hour periods plus an extra 8-hour period for two of the four, 232 wear-hours).

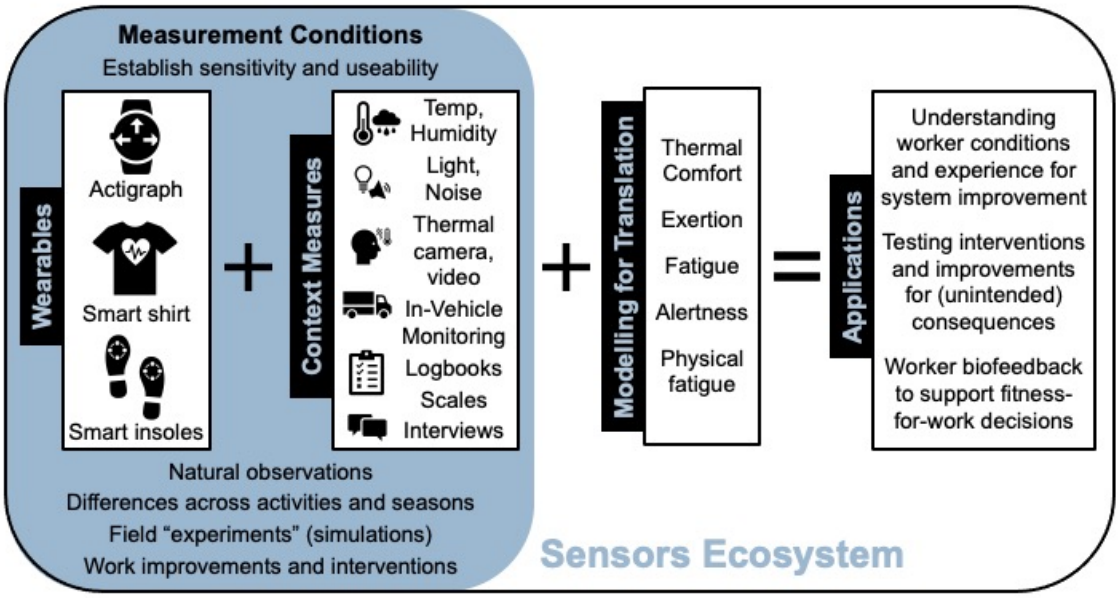


Figure 1.1: Sensors Ecosystem: Summarises the design to support the use of three types of wearable sensors in this operational environment.

Motion sensing insoles (OpenGo Sensor Insoles, Moticon, Germany) were used to monitor gait (2 participants, 30 minutes during service laying, 6.5 hours during meter reading). Concomitant context measures (temperature, humidity, light, and noise, thermal imaging, photography/video, in-vehicle monitoring data, logbooks, scales, and interviews) were collected to aid in analysis and interpretation of sensor data. Standardised, validated modelling approaches were then applied to sensor data in order to translate the data into meaningful metrics. Together, a sensor ecosystem was created in order to establish sensitivity and usability of the wearable sensors (Figure 1.1). Data were collected during water testing (including shifts with an overnight stay), meter reading, and a mock asbestos pipe removal trial, where two participants wore full asbestos removal PPE (hooded coveralls, facemask, gloves, and booties) and spent time in a pre-dug trench cutting a section of PVC pipe. The trial was conducted in winter with low ambient temperatures, and repeated in summer with high ambient temperatures.

1.3 Findings

The findings of these data collection approaches yielded data in five thematic areas:

- **Thermal imaging** - Imaging of micro-environments and head, face, and shoulder surface temperature was sensitive to changes in work and environments and tasks. Imaging under controlled conditions highlighted the benefits of using powered air purifying respirators (PAPR) and ice vests for reducing skin temperatures on the face and neck. The mock pipe removal trial provided a platform to investigate differences in ambient temperature, task length, and PPE. Results supported the thermal benefits of PAPR and ice vests

under summer conditions.

- **Thermal comfort** - Thermal comfort modelling using environmental data in combination with estimations of thermal insulation from clothing and work intensity estimated thermal comfort levels during the mock pipe removal trial in winter conditions that were within recommended ranges. Modelling for summer conditions produced comfort levels well above the recommended range. Models were consistent with thermal sensation and comfort ratings. Results support the use of PAPR and ice vests to provide some beneficial recovery for thermal sensation and thermal comfort under summer conditions.
- **Heart rate and exertion** - Modelling Exertion using relative heart rate (HR) intensity from the biometric shirts yielded results that were sensitive to task differences (e.g. mock trial, meter reading) and sleep periods. Usability was somewhat limited by requirements to reapply electrode gel and a moderate level of data processing and modelling was needed. Nevertheless, HR data supported thermal comfort and thermal imaging findings regarding the discomfort experienced during working summer heat with full asbestos PPE. Findings suggest that working under these conditions may result in physical exertion at high levels of intensity. Findings also support the use of PAPR and ice vests to attenuate heat stress. Further study in larger samples with more in-depth study of PPE combinations using HR monitoring, in combination with other thermal measures would be extremely fruitful.
- **Activity, sleep, and alertness** - Modelling sleep and physical activity patterns using accelerometry and logbooks revealed that compared to workdays, days off were associated with longer sleep periods, lower physical activity levels, lower caffeine consumption, lower stress ratings, and changes to eating patterns. Compared to other workdays, overnight trips and on-call days with call-outs were associated with longer work hours and increases in physical activity, sleepiness ratings, and caffeine consumption. The wrist sensors were low in participant inconvenience, with relatively high usability and a moderate degree of data processing requirements.
- **Pressure sensors and gait** - Smart insole measurement yielded data sensitive to differences in activity (walking, standing, sitting) and work types (service laying, meter reading. Usability was limited by connectivity requirements and the unsuitability of the insoles for certain tasks (involving wet feet or driving). However, since data collection, newer products have been identified that do not have the same limitations and are more suitable for work conditions. Further research with these devices is recommended.

1.4 Conclusions

The study has demonstrated the utility of actigraphs, smart shirts, and smart insoles for modelling physiological stresses associated with different work practices, equipment choices, and work-planning options.

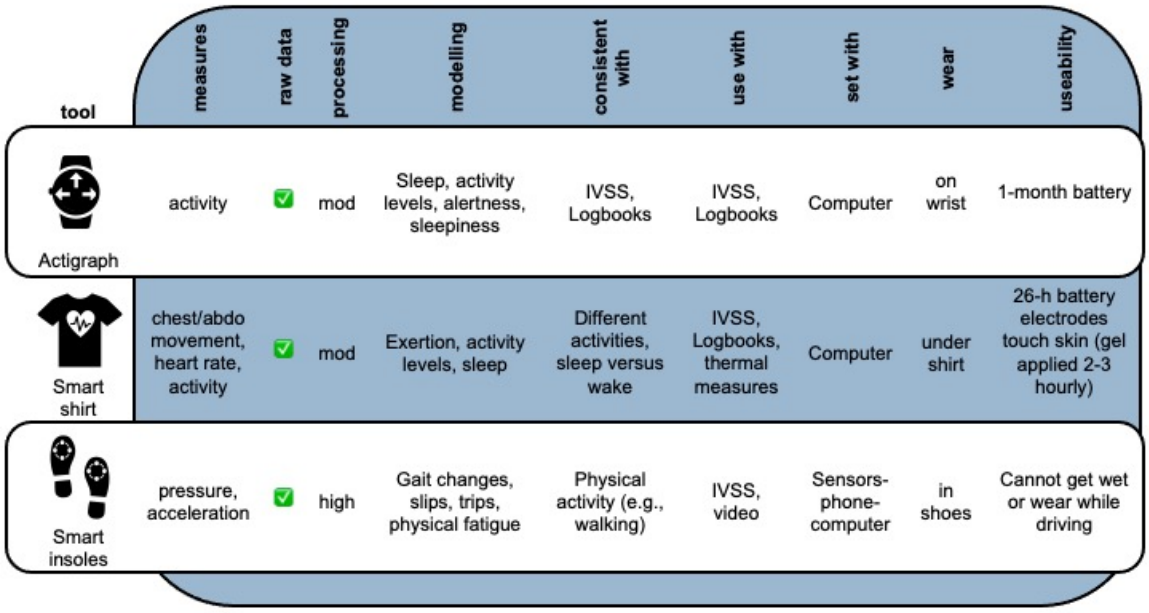


Figure 1.2: Summary of what each wearable device measured, whether raw data was accessible (tick=yes), level of processing required from the raw data (low, mod=moderate, high), algorithms and modelling that can be used to interpret the data, which measures the wearable data were consistent with (showing expected variation as a function of activity level and work task), which measures were used together with each wearable to understand the data in context, the tools required to set and download the wearables, how they were worn, and a description of their usability.

2. Background and Approach

2.1 Project Background

SA Water Corporation is a government-owned water utility employing more than 1500 workers. Field service technicians monitor water quality by collecting samples across more than 4,000 locations in South Australia and Victoria, as well as responding to water quality incidents. In regional areas, field service technicians also conduct pipe removal and repair (and associated tasks), as well as meter reading. They cover daytime operations and rotate through an on-call roster to manage out-of-hours, time-critical work.

As part of their roles, field services technicians undertake frequent periods of driving, often for long distances, to travel between testing locations or incidents. They also conduct physical work that can expose them to potentially hazardous manual tasks, associated with incident and injury. For example, workers may be called to the site of a pipe break, and must work quickly to identify the source, and to rectify the problem in order to restore water supply. This may occur during the day or night, and may involve travel. Intense, manual work, cognitive reasoning to problem-solve under time pressure, and long periods of driving, are all tasks that are particularly vulnerable to the negative effects of fatigue [1, 2]. Fatigue concerns are also generated by extended hours and night work [3, 4]. Due to its relationship with working time and its influences on physical and mental function [5, 6], fatigue is identified as a work health and safety hazard. It is a multifaceted phenomenon, which has been defined as [7]:

> "Fatigue is a physiological state of reduced mental or physical performance capability resulting from: 1) sleep loss; 2) extended wakefulness; 3) circadian phase; and/or 4) workload (mental and/or physical activity) that can impair a person's alertness and ability to perform safety related operational duties."

Due to its multi-faceted nature, fatigue is challenging to measure. Sensing technologies can

provide relevant information to support fatigue management, however, optimal approaches to fatigue monitoring involve outputs from multiple sensors [5, 8].

In this fourth Industrial Revolution, cyber-physical information systems are increasingly used to support workplace safety [9, 10]. Digital technologies, such as wearables, are becoming increasingly affordable and may provide health and safety-related data [5, 11]. While the proliferation of such devices supports their potential, current barriers to effective use include employee concerns about data privacy and confidentiality, employer concerns about compliance with intended sensor use, general concerns regarding level of trust in the data, and potential logistic issues of implementation (e.g. sensor durability) [8, 12]. These barriers to implementation highlight the importance of systematically investigating the human-machine-interaction in cyber-physical systems.

Since fatigue is a multifaceted workplace hazard, fatigue monitoring using inputs from multi-sensor systems is a promising avenue for investigation. In Australia, in any workplace covered by the Work Health and Safety Act [13], fatigue management is a reciprocal responsibility for employers and employees. Decisions about whether an employee is safe to work are frequently self-reported [14]. Research indicates that people's beliefs regarding their fatigue may not align with objective indicators [15]. This could potentially lead to compromised safety if workers are unaware of their fatigue and related performance deficits. A promising solution is to supplement the information that people use to make decisions about fitness-for-work [8].

Such programs can have a direct effect on safety through hazard identification, as well as an important indirect effect through promoting safety conversations. This is part of developing a positive safety culture that focuses on open discussion and reporting, which is critical not only for fatigue management, but for safety more broadly [5, 16, 17]. When considering fatigue in this context, implementation of fatigue monitoring technology should be designed to provide information that supports not only individual worker safety, but also interventions designed to promote safety culture.

SA Water has a clear commitment to further develop their safety culture to increase awareness of exposure to hazards, and to facilitate open discussions about safety. This project provides an opportunity for targeted data collection and analysis to better understand the safety hazards as well as the potential for effective application of sensors to support fatigue management.

2.2 Aims

- To trial a combination of well-established and novel sensing technologies in order to investigate their potential to enhance the safety of workers on site and on the roads;
- To synthesise data from sensors, observations, and interviews, monitoring workers during safety-critical tasks;
- To provide an initial evidence base to integrate sensing technologies to enhance safety of workers carrying out safety critical work through the day and night.

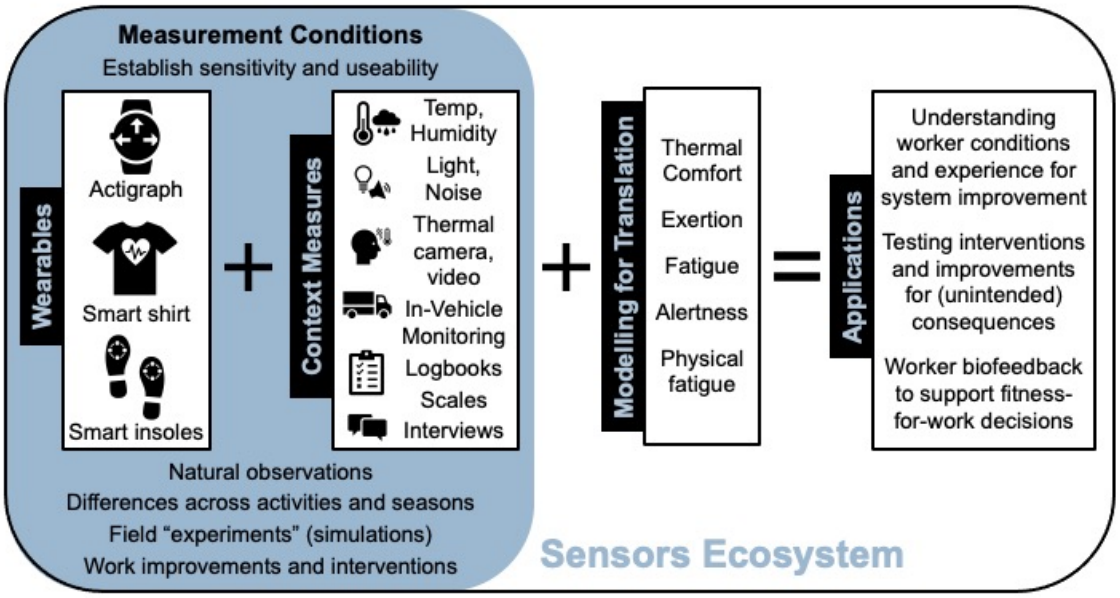


Figure 2.1: Sensors ecosystem design to support the use of three types of wearable sensors in this operational environment.

2.3 Methods

During the trial, field-based staff tested three wearable devices: Wrist actigraphs (indicating sleep and activity patterns), smart shirts (indicating activity and exertion levels), and smart insoles (gait changes as a function of changes in activity and exertion). During the study, physiological data were captured in the field in order to test the usability, sensitivity, and interpretability of these measures in the early detection and intervention of potential safety issues. In particular, we identified the necessary elements within the sensors ecosystem - the elements required to support the use of wearable sensors in this operational environment. In order to test and understand the sensor data, we included concomitant context measures (temperature, humidity, light, and noise, thermal imaging, photography/video, in-vehicle monitoring data, logbooks, scales, and interviews). In addition, we identified validated models to assist in translation and key applications within the workgroups based on their priorities. Therefore, this was a mixed-methods trial with a first-step of in-depth interviews followed by field measurements. A summary of the sensors ecosystem developed during this project is illustrated in Figure 2.1.

The trial involved 21 participants engaged in a broad range of in-field tasks including water sampling, meter reading, service laying, and simulated pipe repair across three work sites between March 2022 and July 2023. Figure 2.2 displays photos of the equipment used. Measurements included interviews (n=21), logbooks (recording work, sleep, thermal comfort, sleepiness, stress, caffeine, and food timing) (n=16 completed 1-4 weeks, total=224 logbook-days) (Figure 2.3). Matching periods of In-Vehicle Safety System (IVSS) data were harvested (measuring location, speed, distance, and timing) for a subset of participants (Figure 2.4). Environmental measures included temperature and humidity, light levels, and thermal imaging of participants and micro-

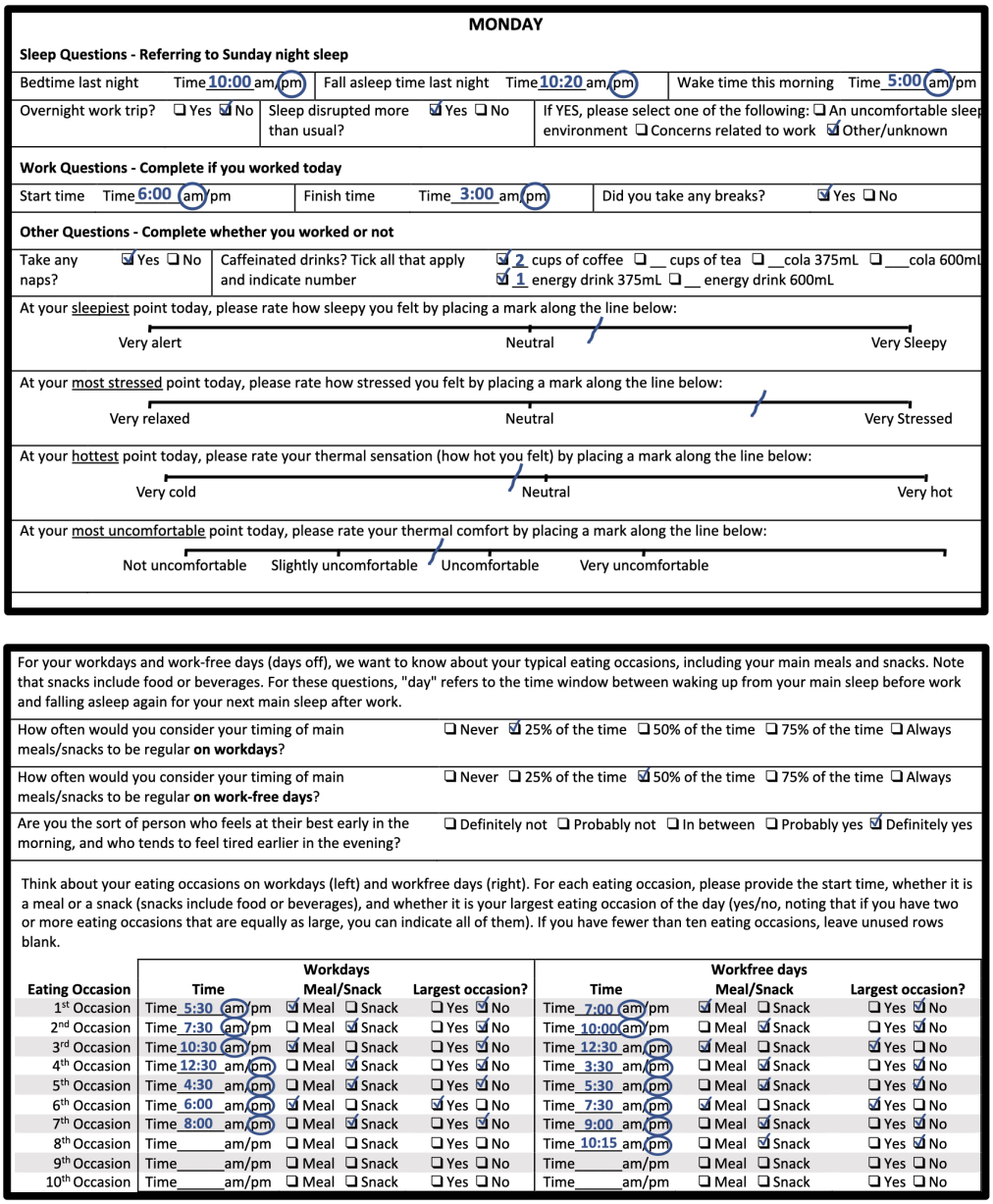
Figure 2.2: Research tools - Smart shirts, smart watches, and environmental measurements.

environments, providing context for three types of wearable sensors:

1. **Wrist sensors** (Geneactiv, ActivInsights, UK) were worn by 16 participants for 1-2 weeks each (total=244 wear-days) to monitor movement. In combination with sleep and work logs, standard actigraphic algorithms were applied to estimate sleep patterns and activity levels [18]. Sleep data were used in a validated biomathematical model to estimate sleepiness and alertness at work.

2. **Biometric smart shirts** (Hexoskin Shirt, Carré Technologies Inc., Canada), with textile-embedded sensors, were worn by four participants for 1-2 36-hour periods and a further 8-hour period for two of the four participants (total=232 wear-hours) to monitor chest and abdominal movement and heart rate. Using standard heart rate models, data were used alongside logbooks and IVSS data to estimate exertion levels during different work activities.

3. **Motion-sensing insoles** (OpenGo Sensor Insoles, Moticon, Germany) were worn by two participants during field work to measure force and pressure distribution. Insole data are identify changes in gait (e.g., precursors to trips and falls), and can be used alongside logbooks and IVSS to understand gait changes as a function of activity and fatigue. One participant was recorded during a 30-minute service-laying procedure, and the other for a dayshift involving meter reading (measured over 6 hours) with concomitant video of meter reading activities.



MONDAY

Sleep Questions - Referring to Sunday night sleep

Bedtime last night Time 10:00 am/pm	Fall asleep time last night Time 10:20 am/pm	Wake time this morning Time 5:00 am/pm
Overnight work trip? ❑ Yes ☑ No	Sleep disrupted more than usual? ☑ Yes ❑ No	If YES, please select one of the following: ❑ An uncomfortable sleep environment ❑ Concerns related to work ☑ Other/unknown

Work Questions - Complete if you worked today

Start time Time 6:00 am/pm	Finish time Time 3:00 am/pm	Did you take any breaks? ☑ Yes ❑ No

Other Questions - Complete whether you worked or not

Take any naps? ☑ Yes ❑ No	Caffeinated drinks? Tick all that apply and indicate number ☑ 2 cups of coffee ❑ __ cups of tea ❑ __cola 375mL ❑ ___cola 600mL ☑ 1 energy drink 375mL ❑ __ energy drink 600mL

At your sleepiest point today, please rate how sleepy you felt by placing a mark along the line below:

Very alert — Neutral — Very Sleepy

At your most stressed point today, please rate how stressed you felt by placing a mark along the line below:

Very relaxed — Neutral — Very Stressed

At your hottest point today, please rate your thermal sensation (how hot you felt) by placing a mark along the line below:

Very cold — Neutral — Very hot

At your most uncomfortable point today, please rate your thermal comfort by placing a mark along the line below:

Not uncomfortable — Slightly uncomfortable — Uncomfortable — Very uncomfortable

For your workdays and work-free days (days off), we want to know about your typical eating occasions, including your main meals and snacks. Note that snacks include food or beverages. For these questions, "day" refers to the time window between waking up from your main sleep before work and falling asleep again for your next main sleep after work.

How often would you consider your timing of main meals/snacks to be regular **on workdays**?	❑ Never ☑ 25% of the time ❑ 50% of the time ❑ 75% of the time ❑ Always
How often would you consider your timing of main meals/snacks to be regular **on work-free days**?	❑ Never ❑ 25% of the time ☑ 50% of the time ❑ 75% of the time ❑ Always
Are you the sort of person who feels at their best early in the morning, and who tends to feel tired earlier in the evening?	❑ Definitely not ❑ Probably not ❑ In between ❑ Probably yes ☑ Definitely yes

Think about your eating occasions on workdays (left) and workfree days (right). For each eating occasion, please provide the start time, whether it is a meal or a snack (snacks include food or beverages), and whether it is your largest eating occasion of the day (yes/no, noting that if you have two or more eating occasions that are equally as large, you can indicate all of them). If you have fewer than ten eating occasions, leave unused rows blank.

	Workdays			Workfree days		
Eating Occasion	**Time**	**Meal/Snack**	**Largest occasion?**	**Time**	**Meal/Snack**	**Largest occasion?**
1st Occasion	Time 5:30 am/pm	☑ Meal ❑ Snack	❑ Yes ☑ No	Time 7:00 am/pm	☑ Meal ❑ Snack	❑ Yes ☑ No
2nd Occasion	Time 7:30 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No	Time 10:00 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No
3rd Occasion	Time 10:30 am/pm	☑ Meal ❑ Snack	❑ Yes ☑ No	Time 12:30 am/pm	☑ Meal ❑ Snack	☑ Yes ❑ No
4th Occasion	Time 12:30 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No	Time 3:30 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No
5th Occasion	Time 4:30 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No	Time 5:30 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No
6th Occasion	Time 6:00 am/pm	☑ Meal ❑ Snack	☑ Yes ❑ No	Time 7:30 am/pm	☑ Meal ❑ Snack	☑ Yes ❑ No
7th Occasion	Time 8:00 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No	Time 9:00 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No
8th Occasion	Time_____am/pm	❑ Meal ❑ Snack	❑ Yes ❑ No	Time 10:15 am/pm	❑ Meal ☑ Snack	❑ Yes ☑ No
9th Occasion	Time_____am/pm	❑ Meal ❑ Snack	❑ Yes ❑ No	Time_____am/pm	❑ Meal ❑ Snack	❑ Yes ❑ No
10th Occasion	Time_____am/pm	❑ Meal ❑ Snack	❑ Yes ❑ No	Time_____am/pm	❑ Meal ❑ Snack	❑ Yes ❑ No

Figure 2.3: Logbook - Upper panel shows daily questions relating to sleep, work, caffeine, sleepiness, stress, thermal sensation and thermal comfort. Lower panel shows a single administration question set about food timing.

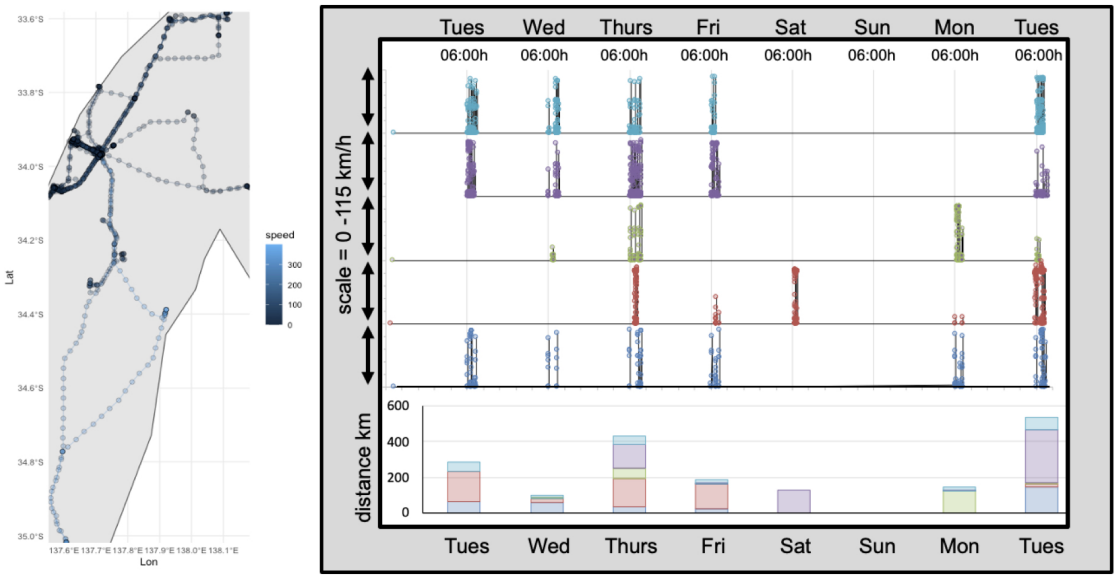


Figure 2.4: In-Vehicle Monitoring System Data - Dataset includes latitude, longitude, speed, and distance travelled. The left panel shows a map of travel with depth of colour representing vehicle speed. The right panel shows speed and distance travelled across eight days for five participants.

2.4 Interviews and Data Collection Co-Design

Interviews were conducted with n=21 employees from three sites (2 metropolitan, 1 regional). At both sites, fatigue while driving was identified as a key safety hazard, heat was identified as a factor that exacerbated fatigue, and sleep was disrupted by work hours and/or work stressors (as well as out of work factors). Other safety priorities differed between metropolitan and regional sites:

- **Metropolitan sites** - Work included water testing. Staff identified overnight shifts (particularly multiple), stress (e.g., perceived time pressure), unanticipated changes to workdays, some jobs with unpleasant conditions as areas of potential focus.
- **Regional site** - Work included water testing, meter reading, and repairs. Staff identified working in the heat with asbestos suits, being on-call, and stress (e.g., responsibility for critical water access) as areas of potential focus.

Findings directly shaped data collection targets and analyses at each site. Protocols and methods were co-designed with SA Water workgroups. In addition to collection of wearable sensor data during typical operations, a mock asbestos pipe removal trial was also designed to simulate a key task identified as an area for heat and fatigue risk. Data collection is summarised in Table 2.1.

The findings of these data collection approaches yielded data in five thematic areas that will be addressed in subsequent sections of this report:

- Thermal imaging - Measuring skin temperatures and micro-environments
- Thermal comfort - Standard modelling
- Heart rate and exertion - Modelling exertion using relative heart rate intensity
- Activity, sleep, and alertness - Modelling sleep and physical activity patterns using accelerometry
- Pressure sensors and gait - Smart insole measurement

Table 2.1: **Summary of the data collected across the project.**

Measures	Info	Regional Data	Metro Data	Total Time
Interviews	30-60 min	n=5	n=16	>11h
Logbooks	work hours, sleep, thermal comfort, sleepiness, stress, caffeine, food timing	Up to 4 x 1 week each, n=6	n=10, 1 week each	224d
Geneactiv	wrist accelerometer	Up to 4 x 1 week each, n=6, (normal ops, meter reading), 2 days, n=2 (meter reading)	n=11, 1 week each	224d
IVSS	lat, long, speed, distance, timing of driving	matching Geneactiv subset	matching Geneactiv subset	151d
Hexoskin	shirts recording HR, movement	4 x 36h periods (n=3, 1 repeated) + 2 x 8h periods	2 x 36h periods (n=1)	216h
Pipe Removal	mock asbestos simulation trial	n=2 x 2 (in winter=30min, in summer=70min)	-	100min
Moticon	insole pressure sensors	30-min period (on-site service laying), full shift (meter reading)	-	6.5h

Notes: IVSS=in-vehicle monitoring system; HR=heart rate; h=hours; d=days; min=minutes

3. Thermal Imaging

THERMAL imaging of participants' head, face, and shoulders was conducted indoors under controlled conditions and also during a simulated asbestos pipe removal trial. Indoor and outdoor trials were conducted during winter and repeated under summer conditions.

Thermal camera images were downloaded from the camera and then pixel-level data were processed through an R package (Thermstats) [19], which converted the data to temperatures taking into account ambient conditions, emissivity, and object distance (Figure 3.1). The data were extracted into a CSV file, with the head and upper body zones selected for analysis.

Figure 3.1: Thermal camera image processing.

3.1 Imaging Under Controlled Conditions

As outlined in the previous chapter, working in the heat wearing asbestos PPE was identified as a key WHS concern. A series of data collection protocols were conducted to investigate the impact of safety masks, air circulators, and coveralls, on skin surface temperature:

- **Protocol 1 - Mask only**. Two participants wore safety masks for 20 minutes inside under temperature controlled conditions (ambient temperature 21°C, relative humidity (RH)=70%). Thermal images of the head, face, and shoulders were taken immediately before and after mask wearing with the participant seated at a distance of 2 m from the photographer.

- **Protocol 2 - Powered air purifying respirator (PAPR)**. Protocol 1 was repeated with four participants who wore the mask indoors (ambient temperature=21.5°C, RH=51%) on two occasions for 20 minutes each. On the first occasion they wore the mask without, and on the second occasion with a PAPR.

- **Protocol 3 - Coveralls, ice vests, and walking outside.** Face and neck images were taken for two participants across a series of PPE changes, conducted during summer. Participants put on coveralls, gloves, and booties and wore the mask with filter only, and then with PAPR added, while walking outside in the summer heat for 20-minute periods (ambient temperatures=21.5-32.5°C, RH=76-31%). This is the level of PPE required for asbestos removal. Participants then repeated this procedure adding an ice vest.

Results of Protocol 1 revealed that the camera was sensitive to differences in body surface temperature as a function of mask wearing. Specifically, increases in temperatures across the face and neck were observed, as well as increases in clothing surface temperatures across the chest and shoulders (Figure 3.2).

Figure 3.3 shows results of Protocol 2. The left panels show the mask with filter only. The right panels show the mask with PAPR. These results suggest that PAPR results in a reduction in skin temperature on the cheeks and around the mouth (between eyeline and lipline).

Showing results of Protocol 3, Figure 3.4 illustrates the increase in face an neck temperatures with the addition of the coveralls, booties, and gloves. PAPR resulted in similar reductions in temperatures between the eye and lip. Ice vests resulted in reductions in shoulder and chest temperatures (white/very light blue zones indicating temperatures lower than 25°C).

Figure 3.5 summarises the results of Protocol 1, 2, and 3, showing the mean temperatures for the upper (focusing on the forehead), middle (between the eyes and lips), and lower (focusing on the neck) thirds of the face and neck for each image. Means are expressed as percentage change from 'Pre' values (shown as zeros in the figures). Mask wearing inside resulted in an increase in face and neck temperatures, with the largest increases seen in the neck (approximately 8%). PAPR resulted in a reduction of temperatures in the upper and middle thirds, but not the lower third. The combination of the ice vest and PAPR resulted in reductions in temperatures across the face and neck.

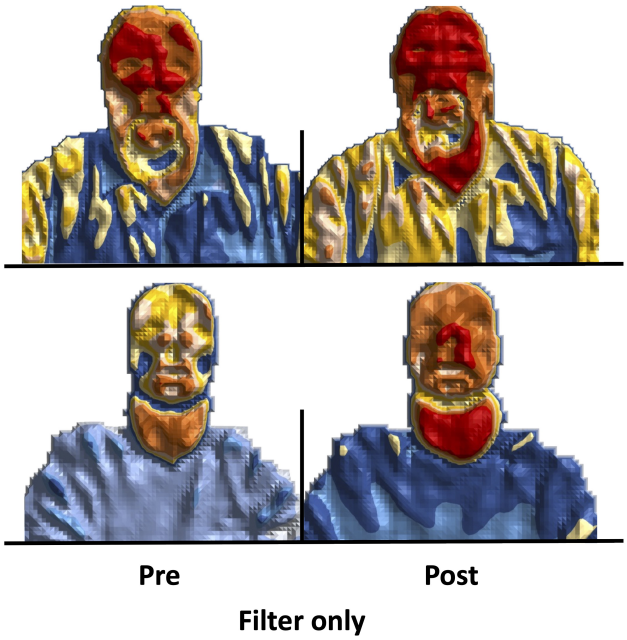


Figure 3.2: **Protocol 1 - Mask only.** Thermal camera image analysis of face and shoulder temperature for participant a (upper) and participant b (lower). Colours range from coldest (blues) through middle temperatures (yellows) to warmest (oranges and reds), with deeper colours indicating higher temperatures within each colour range.

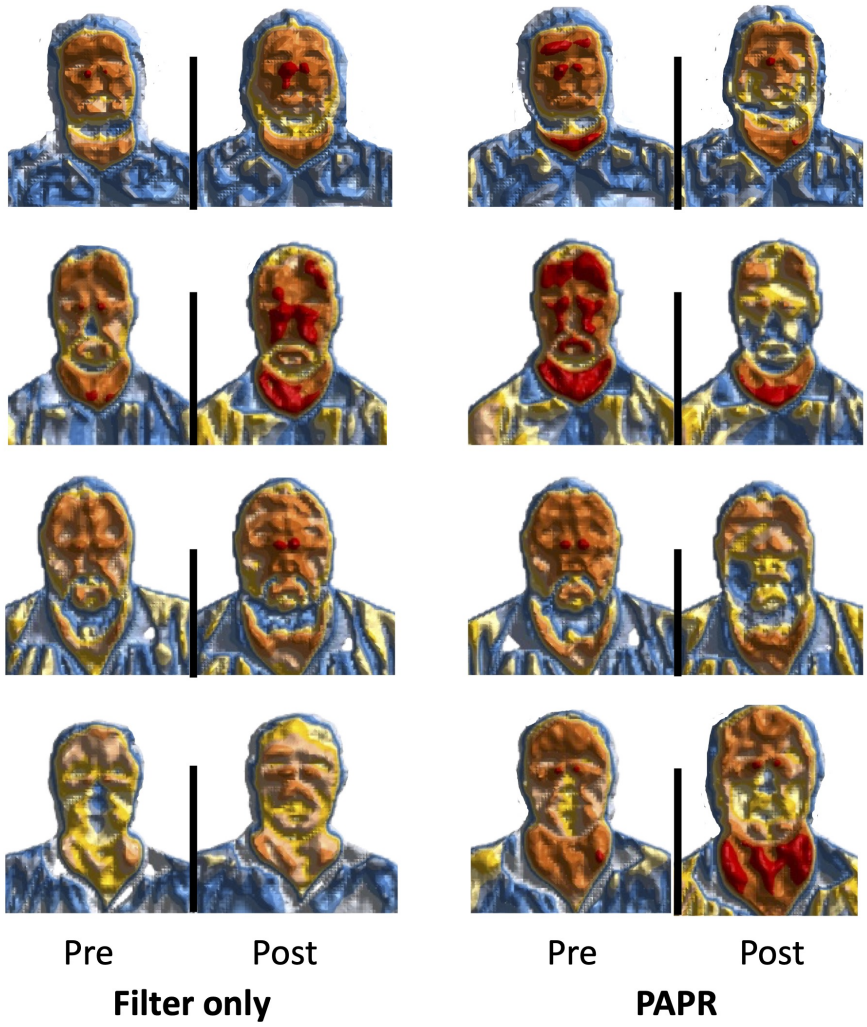


Figure 3.3: **Protocol 2 - Powered air purifying respirator (PAPR).** Thermal camera image analysis of face and shoulder temperature for four participants. Left panels show pre- and post-mask with filter only. Right panels show pre- and post-mask PAPR. Colours range from coldest (blues) through middle temperatures (yellows) to warmest (oranges and reds), with deeper colours indicating higher temperatures within each colour range.

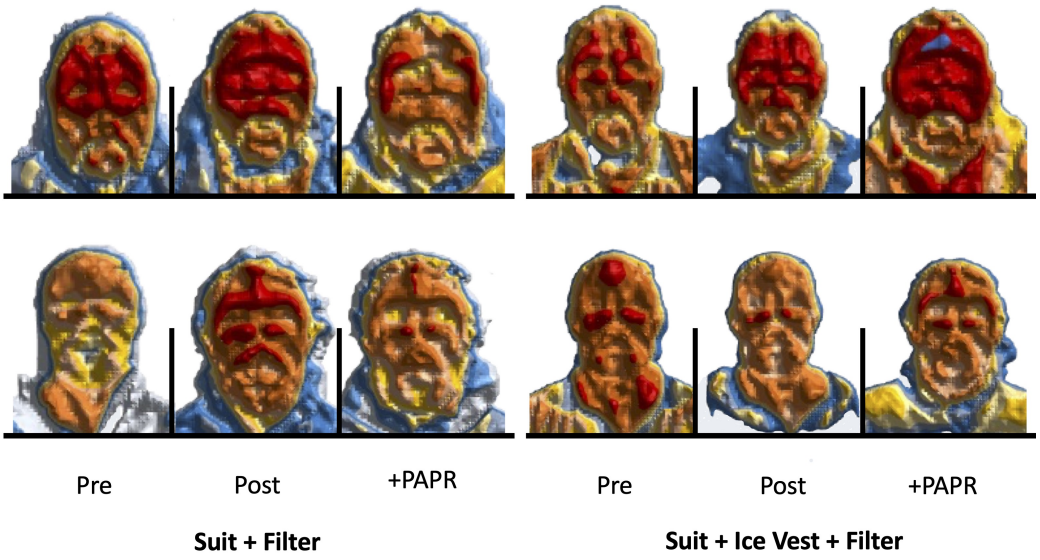


Figure 3.4: **Protocol 3 - Coveralls, ice vests, and walking outside.** Thermal camera image analysis of face and shoulder temperature for participant a (upper) and participant b (lower). From left to right, panels indicate pre- and post-mask wearing with suit and filter only then with PAPR added, followed by suit and ice vest with filter only then with PAPR added. Participants walked outside in the summer weather for 20-minute periods while wearing the PPE between imaging. Colours range from coldest (blues) through middle temperatures (yellows) to warmest (oranges and reds), with deeper colours indicating higher temperatures within each colour range.

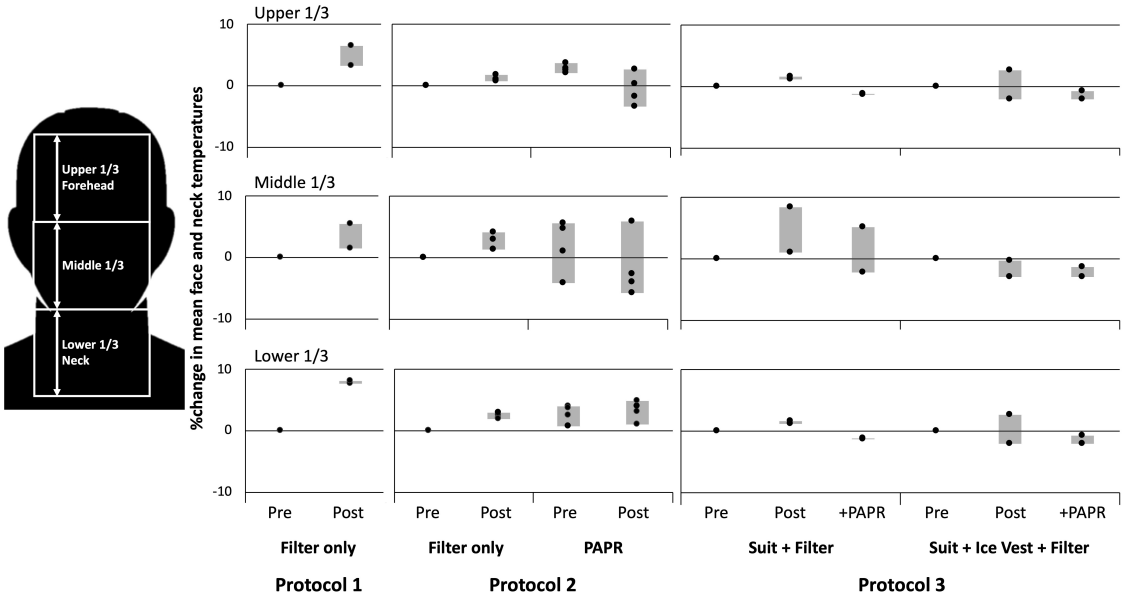


Figure 3.5: **Mean temperatures for Protocol 1, 2, and 3.** Thermal camera image analysis of face and shoulder temperature for two participants across each protocol, from left to right. Temperatures are averages for upper, middle, and lower thirds of the face and neck.

3.2 Mock Asbestos Pipe Removal Trial

Simulation of an asbestos pipe removal under controlled conditions was set up to facilitate replication under different ambient conditions (Figure 3.6). Two participants wore full asbestos removal PPE (hooded coveralls, facemask, gloves, and booties) and spent 20- to 30-minute periods in a pre-dug trench cutting a section of PVC pipe across two conditions:

- **Winter conditions:** The trial began at 9:09h on a day in winter, with a relatively low ambient temperature for the region (17.5°C) and a high relative humidity. It began raining during the trial. It was overcast, with light levels at around 300 lux, with a median ground temperature of 16.4°C (measured using thermal images of the surrounding soil). Thermal imaging of participants' head, face, and shoulders was conducted immediately prior and immediately following (as soon as participants removed their mask) the pipe cutting simulation.

- **Summer conditions:** The trial was then replicated during summer, with relatively high ambient temperature (33.9°C), and relative humidity at approximately 20%. The trial began at 14:27h and thermal images were taken following 20 minutes of pipe-removal with mask and filter only, following 20 minutes with PAPR added, and finally following 30 minutes with PAPR plus an ice vest. Conditions were sunny, with ground temperatures (measured using thermal images of the surrounding soil) ranging from 31.7 to 61.0°C.

Thermal imaging revealed differences in body surface temperature as a function of ambient

Season (start time)	PPE	Start		Finish		Duration (mins)	Conditions
		Ambient (°C)	RH (%)	Ambient (°C)	RH (%)		
Winter (9:08h)	PAPR	17.5	70	15.5	82	30	
Summer (14:27h)	Filter	33.3	20	33.7	20	20	
	PAPR	33.8	20	34.1	12	20	
	PAPR +ICE	34.1	12	33.7	20	30	

Figure 3.6: Trial Protocol.

temperatures and changes in PPE while conducting a simulated pipe removal. There were clear increases in surface temperatures across the head and neck in summer compared to winter (Figure 3.7).

Mean temperatures for each trial in the upper, middle, and lower thirds of the face and neck are shown in Figure 3.8. Increased ambient temperatures in summer combined with a longer period conducting simulated work resulted in temperature increases across the face of up to 32%. The largest increases were across the middle of the face. While temperatures increased across the trials in summer, which is not surprising due to the increased time on task, the application of PAPR resulted in a further, 2-3% increase in the upper and middle thirds, and a 2-3% decrease in the lower third of the face and neck. It would be highly beneficial to replicate this trial while counterbalancing the order of PPE worn in order to tease out the effects of PPE, time on task, and time of day.

3.3 Key Points

Exploration of thermal imaging of participants' face, shoulders, and neck, and work micro-environments revealed that:

- Thermal imaging can be used to capture surface temperatures in the field;
- Changes in skin temperature can provide information about physiological responses to work environments and tasks;
- The mock trial provided a platform for investigating differences in ambient temperature, task length, and PPE.
- Results support the thermal benefits of PAPR and ice vests.
- Further research to examine findings in a larger sample and differentiate the impact of time-on-task and PPE would be of benefit.

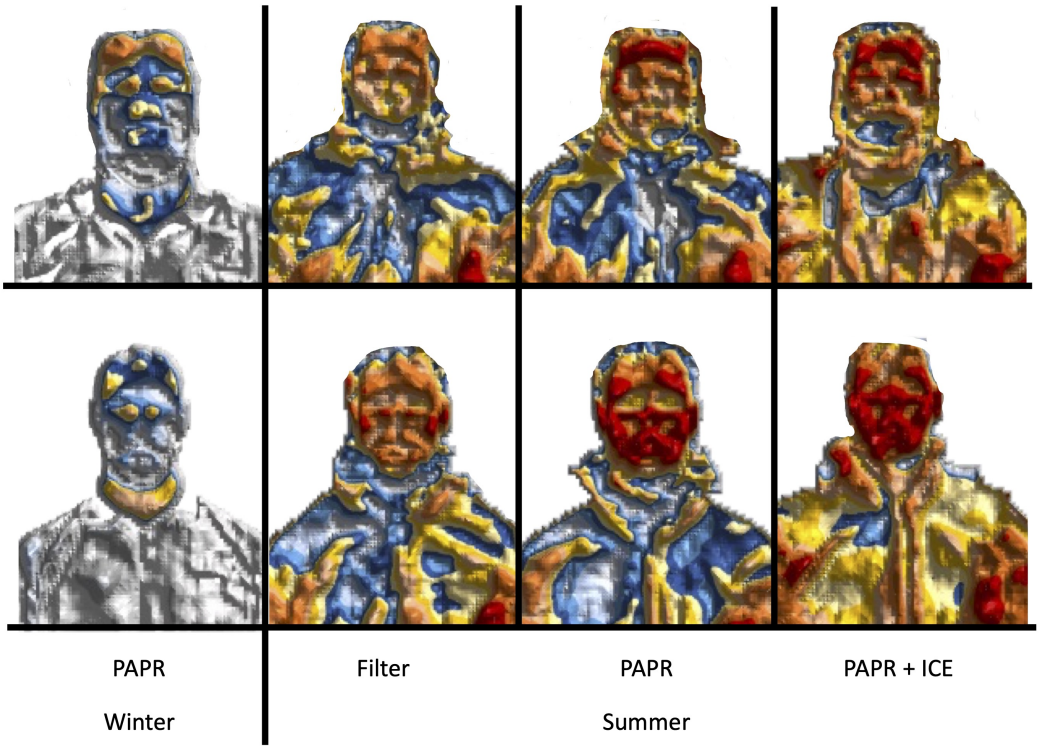


Figure 3.7: **Mock asbestos pipe removal trial during winter and summer conditions.** Thermal camera image analysis of face and shoulder temperature for participant a (upper) and participant b (lower). From left to right, images were taken following the mock pipe removal in winter, then in summer. Summer images were taken following 20-30 minutes cutting pipe with suit and filter only, suit and filter plus PAPR, followed by suit and ice vest with filter only then with PAPR added. Colours range from coldest (blues) through middle temperatures (yellows) to warmest (oranges and reds), with deeper colours indicating higher temperatures within each colour range.

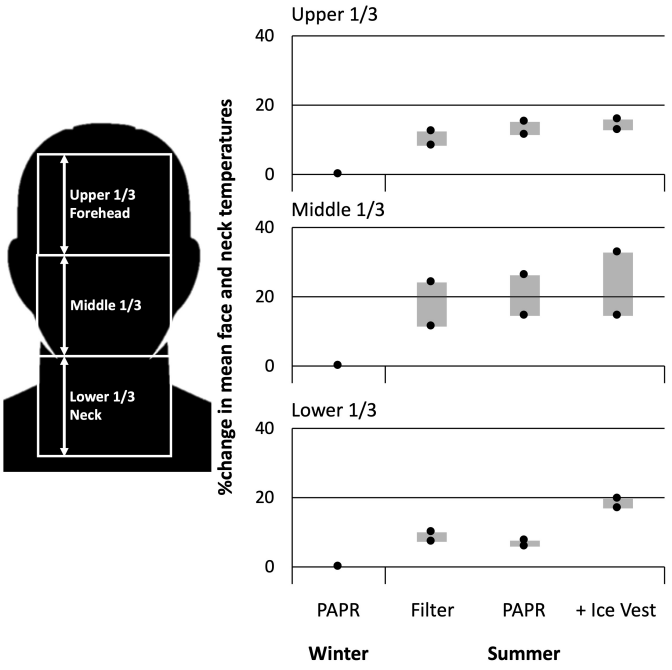


Figure 3.8: **Mock asbestos pipe removal trial during winter and summer conditions.** Thermal camera image analysis of face and shoulder temperature for two participants across winter and summer trials, from left to right. Temperatures are averages for upper, middle, and lower thirds of the face and neck.

4. Thermal Comfort

HEAT was identified as a key risk factor for field services technicians. In the previous chapter, a mock asbestos pipe removal trial was described, with thermal imaging suggesting changes in skin temperature as a function of the season, task, and PPE in particular. In addition to the physiological measures outlined, participants completed ratings of thermal comfort. These ratings were included as part of the pipe removal trial, and also in daily logbooks. Validated measurements included:

- **Thermal sensation** - Measured using a modified ASHRAE 200 mm Visual Analogue Scale [20]. The scale ranges from "Very cold" (0 mm) through "neutral" (100 mm) to "Very hot" (200 mm). The participant places a mark on the continuous line and the result is measured in mm.
- **Thermal comfort** - Measured on a 4-point scale ranging from "not uncomfortable" [0 mm], "slightly uncomfortable" [40 mm], "uncomfortable" [80 mm], to "very uncomfortable" [120 mm] [21]. The participant places a mark on the continuous line and the result is measured in mm.

Thermal sensation was measured immediately before and after the mock asbestos pipe removal trials in winter (with PAPR) and in summer (with filter only, PAPR, and PAPR + ice vests). Ratings showed increases in perceived heat following all trials wearing asbestos PPE. Post-trial, participants rated the filter only trial as hottest, with use of PAPR and the combination of PAPR and ice vests bringing the perceived temperature back down to winter levels (Figure 4.1).

The concepts of thermal sensation and thermal comfort are related but independent. That is, feeling hotter typically (but not always) coincides with higher levels of discomfort. This relationship can be seen in (Figure 4.2), which shows that as heat ratings increased, discomfort ratings also increased. This figure shows ratings during the Protocols 2, and 3, and the winter and summer trials relative to a "typical zone" for ratings. This "typical zone" was calculated as the average of all daily ratings from logbooks across the full study (May, June, July, August,

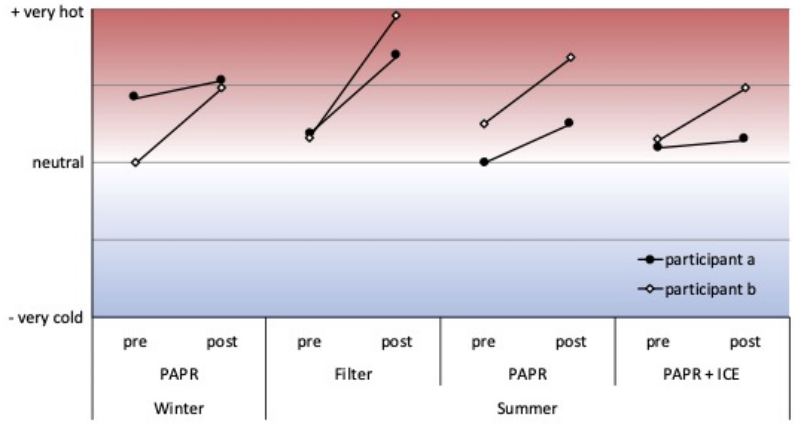


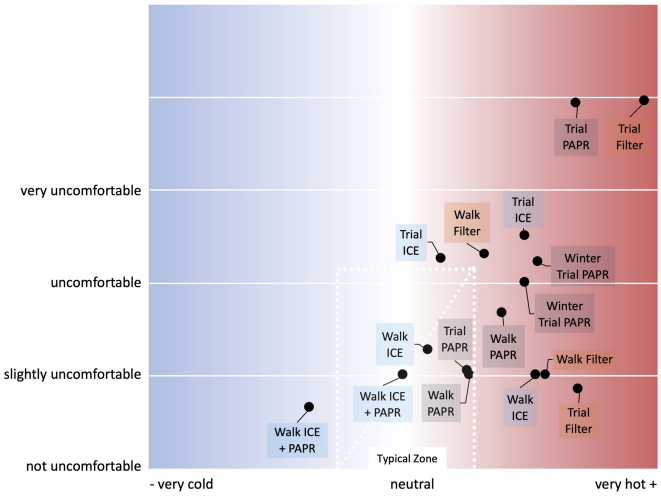
Figure 4.1: Thermal comfort ratings for two participants before and after the winter and summer mock asbestos trials. PAPR=Powered air purifying respirator, ICE=Ice vests.

and September 2022, and March 2023 n=174 days), plus and minus one standard deviation. On the right of the figure, relative rankings are shown for sensation and comfort. Overall, the summer trials were experienced as the hottest and least comfortable, with the combination of ice vests and PAPR producing the coolest and most comfortable ratings.

4.1 Modelling Thermal Comfort

In order to further understand the relationships between ambient conditions, PPE, and work task, data were used to model thermal comfort. Thermal comfort modelling uses validated models of the relationship between clothing insulation, metabolic rate, radiant temperature, air temperature, air speed, and humidity, to estimate Thermal Comfort Predicted Mean Vote (PMV), which ranges from -3 (Cold), to +3 (Hot) (Figure 4.3). In addition to PMV, the percentage of those dissatisfied with their level of thermal comfort is calculated (PPD). A comfort zone is delineated where PMV is between -0.5 and +0.5, and the percentage dissatisfied falls below 10% [22, 23]. It is important to note that thermal discomfort does not mean that the person is necessarily experiencing performance impairment or safety implications. However, the likelihood of impacts for performance and safety increases as conditions move further outside comfortable limits [24].

The additional thermal insulation from asbestos PPE can be estimated from studies examining the thermal properties of different clothing ensembles [25]. Thermal insulation is measured in Clo units, with 0 Clo equating to someone without clothing, and 1 Clo representing the thermal insulation required for someone to remain comfortable at rest, inside, with room temperature at 21 degrees Celsius and low air movement and less than 50% humidity. The total insulation is the sum of the insulation from individual items. For our study participants, work clothing likely



Sensation (hottest)

Protocol	PPE
summer trial	SUIT+FILTER
summer trial	SUIT+FILTER
summer trial	SUIT+PAPR
summer walk	SUIT+FILTER
winter trial	SUIT+PAPR
summer walk	ICE VEST
winter trial	SUIT+PAPR
summer trial	ICE VEST+PAPR
summer indoor	SUIT+PAPR
summer walk	SUIT+FILTER
summer indoor	SUIT+PAPR
summer trial	SUIT+PAPR
summer trial	ICE VEST+PAPR
summer walk	ICE VEST
summer walk	ICE VEST+PAPR
summer walk	ICE VEST+PAPR

Comfort (most uncomfortable)

Protocol	PPE
summer trial	SUIT+FILTER
summer trial	SUIT+PAPR
summer trial	ICE VEST+PAPR
summer walk	SUIT+FILTER
summer trial	ICE VEST+PAPR
winter trial	SUIT+PAPR
winter trial	SUIT+PAPR
summer indoor	SUIT+PAPR
summer walk	ICE VEST
summer trial	SUIT+PAPR
summer walk	SUIT+FILTER
summer indoor	SUIT+PAPR
summer walk	ICE VEST
summer walk	ICE VEST+PAPR
summer trial	SUIT+FILTER
summer walk	IICE VEST+PAPR

Figure 4.2: **Thermal sensation and comfort ratings**. Left Panel - Scatterplot of ratings during Protocol 2 (summer indoor), Protocol 3 (summer walk) and the winter and summer mock asbestos trials. The typical zone shows the mean plus and minus one standard deviation across all workdays from the log books. Right Panel shows the ranking of each protocol and PPE combination by thermal sensation (from hottest to coldest) and thermal comfort (from most to least uncomfortable).

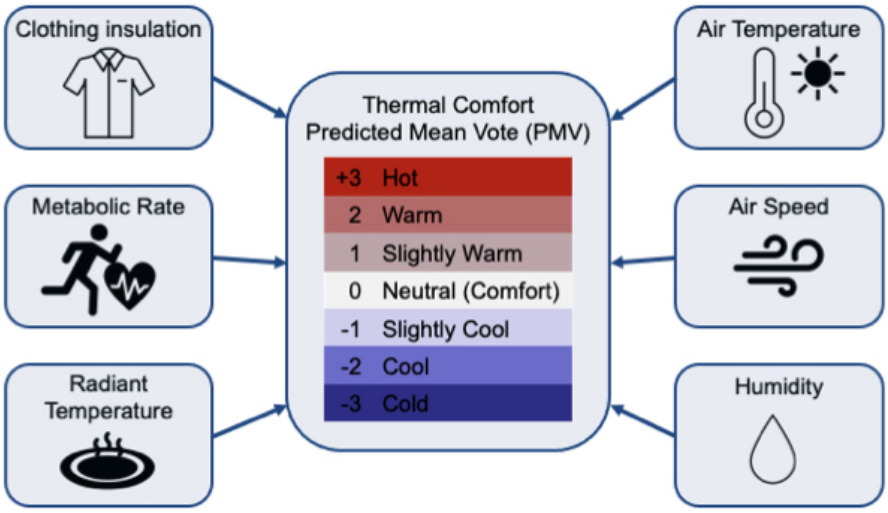


Figure 4.3: Modelling thermal comfort.

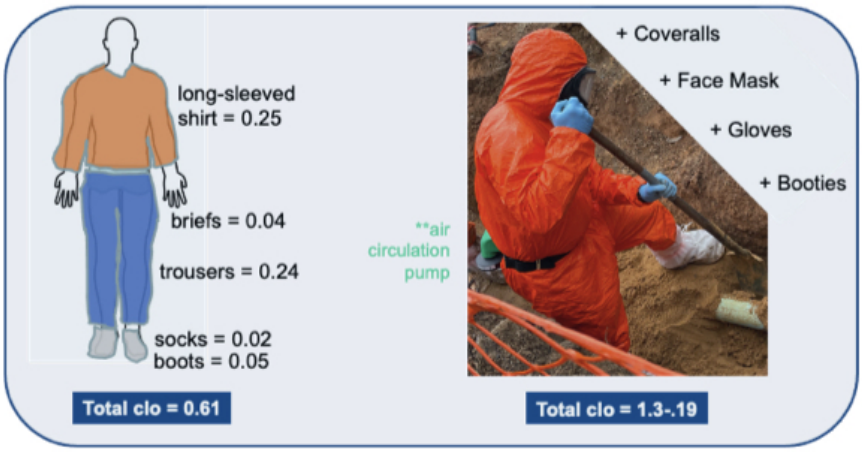


Figure 4.4: Estimating thermal insulation from clothing.

represents 0.61 Clo, with the addition of PPE increasing this value to somewhere between 1.3 and 1.9 Clo, without factoring in air movement from the circulation pump (Figure 4.4).

Results of thermal comfort modelling of the pipe removal trial comparing winter and summer conditions are shown in (Figure 4.5). The figure shows the modelled PMV and PPD for three levels of clothing insulation: (1) standard (without PPE) = 0.61 Clo, (2) +light (most conservative estimate of the added insulation from PPE) = 1.3 Clo, and (3) +mid (middle of the range for the added insulation from PPE) = 1.5 Clo. These are shown for:

- **Winter trial conditions**, with air temperature, relative humidity, and reflected temperature taken from measurements during the pipe removal trial in June.
- **Predicted summer conditions**, estimated from Bureau of Meteorology (BOM) recorded conditions for the area during summer (at 3 pm). Since interviews highlighted the potential added reflected heat on road surfaces, models are shown for soil temperature estimates from February [26], and maximum asphalt temperatures [27].
- **Summer trial conditions**, with with air temperature, relative humidity, and reflected temperature taken from measurements during the pipe removal trial in March.

For these models, air velocity was set at the default 0.15 m/sec, and metabolic rate was set conservatively at 2.6 METs, which indicates the relative rate at which calories are burnt during light-heavy housework (as a relative comparison, sitting quietly = 1, light activities $<$ 3, moderate intensity activities = 3-6, and vigorous activities $>$ 6 METs) [28].

The modelling suggests that under conditions during the winter pipe removal trial, the addition of the PPE increased thermal comfort to within recommended values. In contrast, PMV and PPD were well-outside comfortable, in the hot range, for predicted summer conditions and actual conditions as measured during the summer pipe removal trial.

	Air Temp (°C)	RH (%)	Reflected Temp (°C)		clo	Std Eff Temp (°C)
Winter Trial[a]	16.5	75	min	13.6	std 0.61	21.5
					light 1.3	31
					mid 1.5	32.3
			max	17.7	std 0.61	22.8
					light 1.3	31.8
					mid 1.5	32.7
Summer Prediction[b]	38	13	min	29[c]	std 0.61	32.6
					light 1.3	36.8
					mid 1.5	37.8
			max	62[d]	std 0.61	-AEV-
					light 1.3	-AEV-
					mid 1.5	-AEV-
Summer Trial[e]	33.9	14	min	31.7	std 0.61	31.8
					light 1.3	36.1
					mid 1.5	37.2
			max	61	std 0.61	-AEV-
					light 1.3	-AEV-
					mid 1.5	-AEV-

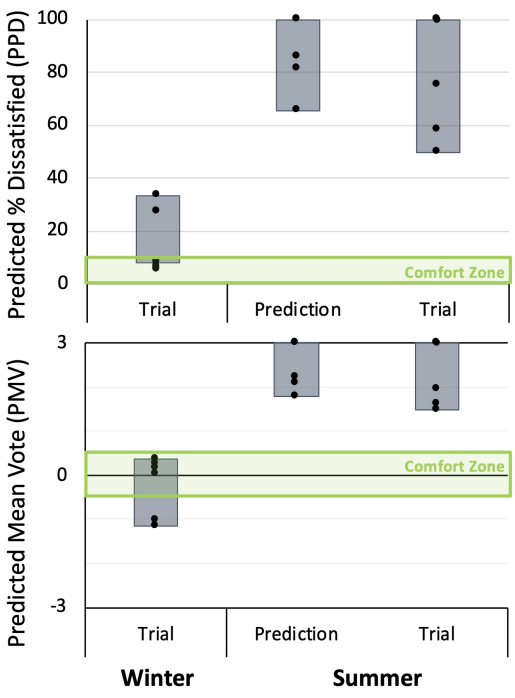


Figure 4.5: **Modelling thermal comfort [22] the mock asbestos pipe removal trial in winter compared to summer conditions.** Left Panel - Modelling for the winter trial, predicted summer values using literature estimates, and values for the summer trial. Right Panel - Predicted Percentage Dissatisfied (PPD) and Predicted Mean Vote (PMV) scores. Notes: std=standard; light=light coverall; mid=mid coverall; mets=2.6 (average across whole activity), light-heavy housework, Jette et al., 1990 [28]; Air velocity at default = 0.15 m per sec; [a]conditions from readings during winter mock asbestos trial, [b]from BOM conditions 3pm; [c]Soyan et al., 2020 [26]; [d]Austroads, 2022 [27]; [e]conditions from readings during summer mock asbestos trial, AEV=above estimable values.

4.2 Key Points

Modelling thermal comfort under winter and summer conditions for a pipe removal with asbestos PPE revealed that:

- Collection of environmental data in combination with estimations of thermal insulation from clothing and work intensity can facilitate thermal comfort models for work tasks;
- Conditions during the winter pipe removal trial resulted modelled thermal comfort levels, as indicated by Predicted Mean Vote and Predicted Percentage Dissatisfied, that were within the recommended range. However, summer conditions were well outside comfort zones;
- The modelling was in line with thermal sensation and comfort ratings;
- Use of PAPR and ice vests are likely to provide some beneficial recovery for thermal sensation and thermal comfort.

5. Heart Rate and Exertion

5.1 Modelling Exertion using Relative Heart Rate Intensity

The Hexoskin shirts yielded heart rate (HR) data while participants were performing different work tasks. One application of HR data is through modelling intensity to estimate exertion. HR is often converted to a percentage of maximum HR using a standardised equation [29]. This is usually done in the context of sports, however, Table 5.1 shows a method for understanding the effects in each of the delineated intensity bands developed for construction workers. Zones 1-3 are seen as physiologically acceptable. HR will likely fluctuate across these zones during a typical work period, depending on the physical characteristics of each task. Performance may be influenced negatively in zones 4 and 5 as workers may become worried and reactive, or frantic and disconnected [30].

Table 5.1: **Relative Intensity Bands for Heart Rate converted into a % of maximum.** Adapted from [30].

Intensity Band	Emotional Zone	Feelings in Zone
90-100%	Red	Out of control, frantic, total panic, disconnected, emergency
80-90%	Distress	Worried, anxious, angry, scattered, fearful, reactive
70-80%	Performance	Focused, in the flow, in my element, positive stress
60-70%	Productivity	High concentration, effective, prolific
50-60%	Safe	Meditative, relaxed, affirming, regenerative, comfortable, compassionate, peaceful

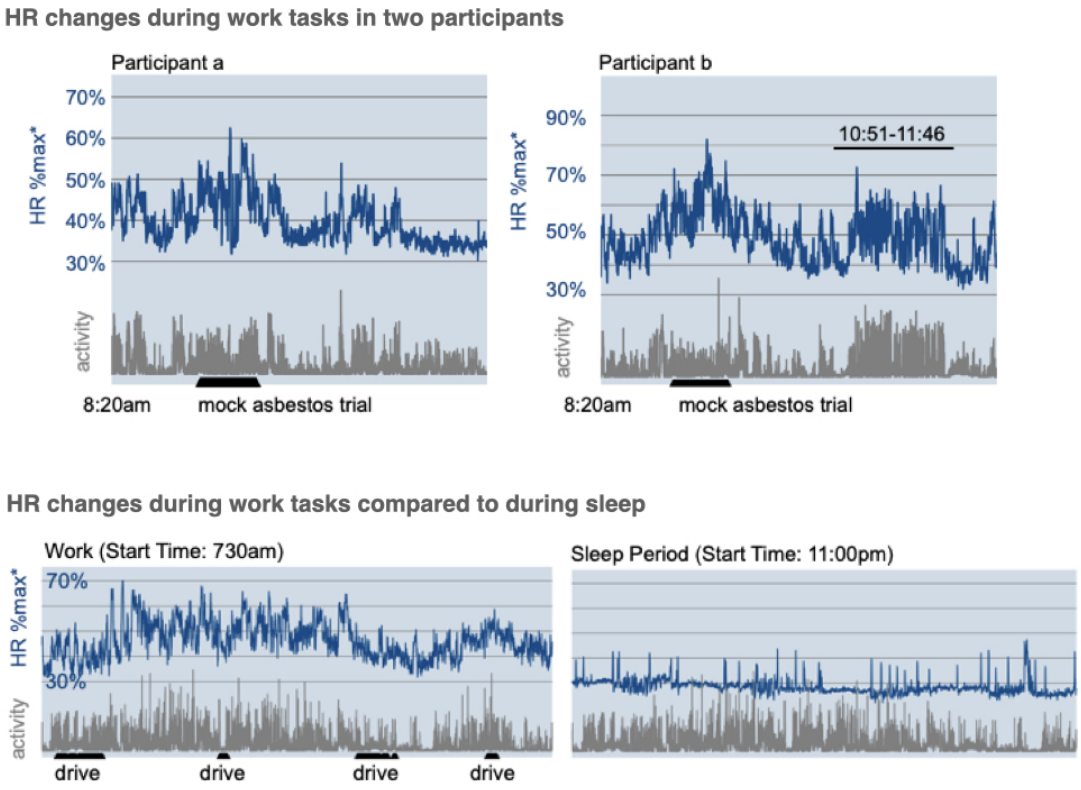


Figure 5.1: Hexoskin HR (blue) and movement (grey) for Participant a (left) and b (right).

5.2 Heart Rate Changes during Work and Sleep

Figure 5.1 show HR (blue) expressed as a percentage of maximum and movement (grey) from the Hexoskin shirts across time for two participants on the shift where the mock asbestos pipe removal trial was conducted. Increases in movement and HR can be seen during the trial. For participant b, a period of increased activity during the late morning can also be noted, when this participant commenced meter reading activities.

Figure 5.1 also shows that the Hexoskin is sensitive to expected differences between sleep and wake, such that compared to average HR on workdays overall (Mean=86.7 bpm, standard deviation (SD)=13.2) is lower while driving (Mean=78.1 bpm, SD=9.5) and lower again during sleep (Mean=52.9 bpm, SD=5.5).

A summary of HR data is provided in Figure 5.2. The left panel shows that mean HR during the mock asbestos trial was higher in summer compared to winter. Mean HR during the trials were also higher than time-matched data taken from other workdays at the same time of year. The middle panel shows the distribution of heart rate zones (calculated as described in Table 5.1). The proportion of time spent in higher heart rate zones was higher in summer. The increase

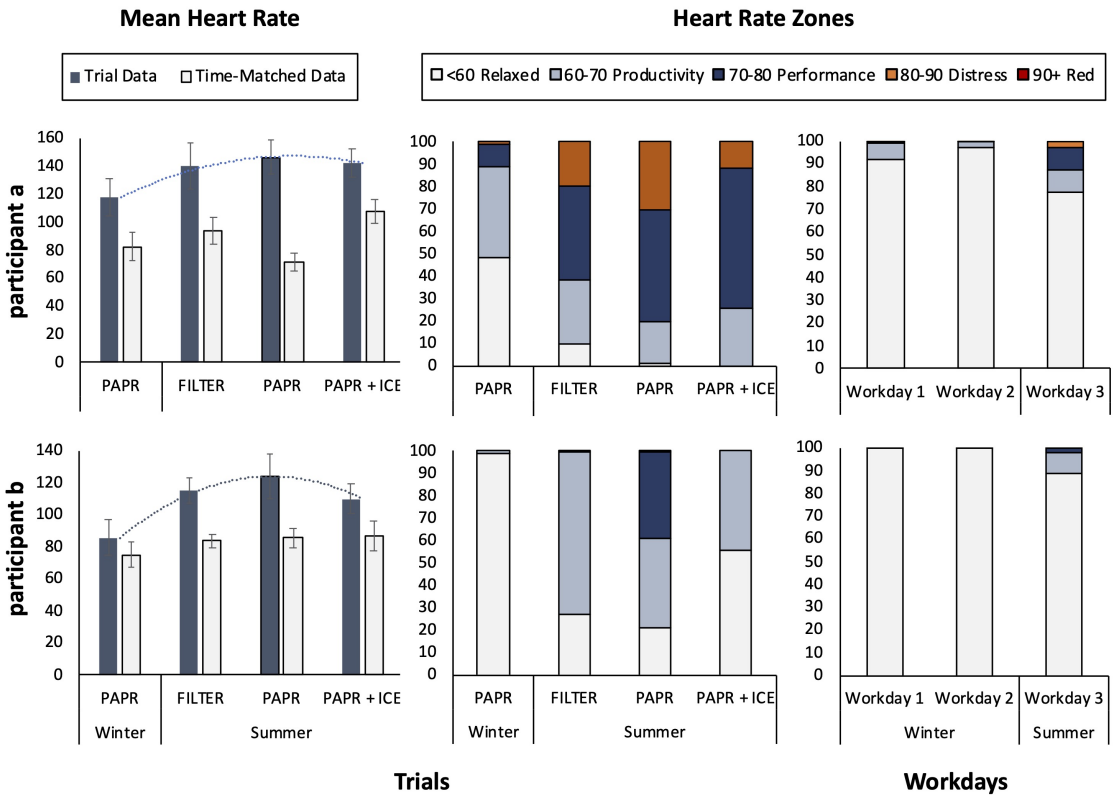


Figure 5.2: Average Hexoskin HR data (left) and distribution across %HRmax Bands (right) for two participants (a and b) across the mock asbestos trials in winter and summer and across whole workdays. Left Panel - Mean (and standard deviation) HR during the trials and during time-matched periods from other workdays at the same time of year. Middle Panel - HR zones across the trials. Right Panel - HR zones across three whole workdays (two in winter and one in summer).

appears somewhat attenuated by the combination of PAPR and ice vests, despite the increasing time on task. For participant a, increases in HR included time in the "distress" zone. The proportion of time spent in higher HR zones was increased during the trial relative to typical workdays (right panel).

It would be of benefit to conduct further research with a larger sample and closer examination of the impact of different combinations of PPE, as well as different lengths of time on task.

5.3 Key Points

Modelling exertion using heart rate revealed that:

- Heart rate (HR) collected using Hexoskin Smart Shirts was sensitive to differences in task,

and sleep/wake status;

- Converting HR to an intensity measure provides a functionally interpretable metric;
- The Hexoskin shirts require application of gel onto the electrodes every 2-3 hours, which is a limitation to their usability;
- Nevertheless, HR data supported thermal comfort and thermal imaging findings regarding the discomfort experienced during summer heat with full asbestos PPE. Findings suggest that working under these conditions may result in physical exertion at high levels of intensity. Findings also support the use of PAPR and ice vests to attenuate heat stress. Further study in larger samples with more in-depth study of PPE combinations using HR monitoring, in combination with other thermal measures would be extremely fruitful.

6. Activity, Sleep, and Alertness

SMART watches are becoming increasingly common. Many of these watches contain accelerometers that measure movement. Research grade versions contain triaxial accelerometers that, in conjunction with validated algorithms, can be used to estimate patterns in sleep and physical activity [8, 18, 31]. Figure 6.1 displays Geneactiv data across three 24-hour periods (from midnight to midnight) for one participant. Their movement data are shown by the blue line. Using participant logbooks, researchers entered the time participants reporting that they fell asleep and woke up each day. A standard algorithm was then applied to identify sleep period time based on movement.

In the figure, sleep is shown in grey. For this participant, sleep occurs during the nighttime hours, and wake time was approximately 5 am on Monday, 230 am on Tuesday, and 530 am on Wednesday. Application of a further algorithm allows us to measure waking during the sleep period, yielding sleep efficiency, which represents the percentage of time spent asleep during a sleep period.

Movement during the wake period can then be categorised into standard activity bands (sedentary, light, moderate, and vigorous). This participant displays intermittent periods of moderate to vigorous physical activity, increasing in the afternoon, followed by more sedentary behaviour leading up to sleep time.

Sleep and physical activity patterns from smart watches can be used to model health and safety at work in the short term (sleepiness and reduced performance effectiveness), and longer term (chronic patterns contributing to changes in health profile).

6.1 Modelling Alertness using Sleep Data

Biomathematical models of alertness, sleepiness, or effectiveness have been developed using established understanding of our sleep and circadian biology to estimate how someone will feel

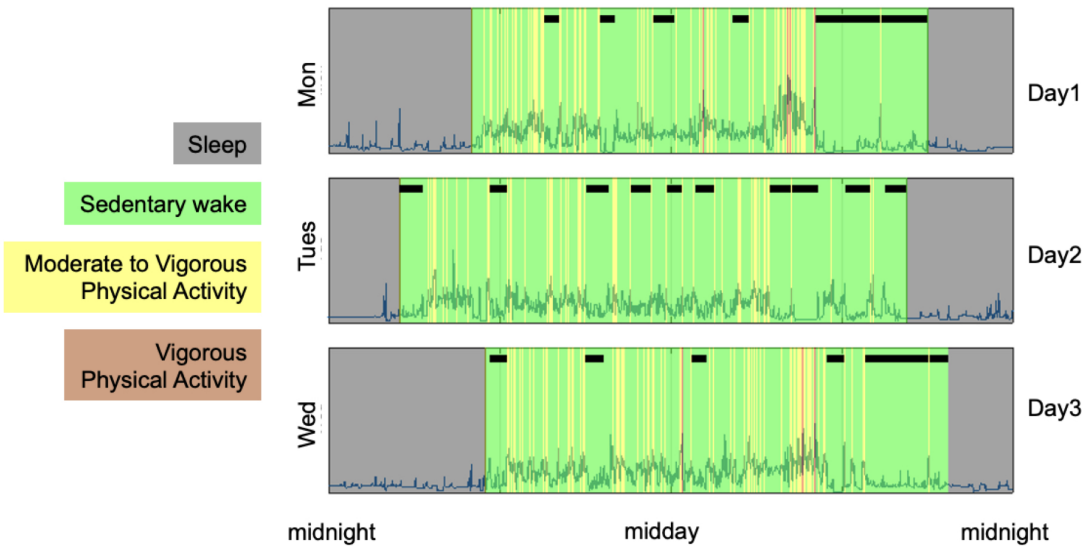


Figure 6.1: Using Geneactiv to estimate sleep and physical activity.

and perform across a work period or a schedule [32, 33, 34]. Figure 6.2 illustrates an example model [35], using data from the participant shown in Figure 6.1. The left panel displays a model of changes in alertness across time as a function of sleep and wake. The model uses inputted sleep period time from the actigraphy analyses (shown in the grey shading). Consistent with Figure 6.1, we can see the shortened sleep on Monday night as a function of the very early waking (230 am) on Tuesday morning. The green sinusoid on the figure represents our circadian (24-hour) rhythm, which is present in many of our physical and mental functions (e.g. heart rate, core body temperature, hormone levels, alertness, attention, mood). There is a low (or nadir) in the early hours of the morning, and a peak prior to typical bedtime. This circadian rhythm works in concert with our sleep drive, shown in blue, which is stronger with increasing time awake and is dissipated by sleep [34].

Combining circadian and sleep drive processes with knowledge of sleep period timing and length, the model produces an alertness estimate [35] (in red), which increases across the day, peaking in the early evening, with a drop following typical bedtime. Looking at the percentage change in the model outputs, alertness and sleepiness, across these three weekdays relative to Sunday, we can see the impact of the short sleep on Monday night with the early wake on Tuesday morning. Alertness is reduced by more than 10% on Tuesday relative to Sunday. The participant goes to bed a little earlier on Tuesday night and wakes a little later on Wednesday morning, leading to some recovery in alertness, though with a remaining deficit relative to Sunday.

The example model used here, the Fatigue Impairment Performance Simulator (FIPS) [35, 36], is one of many available models that work on the same fundamental processes described above [32, 33, 34]. FIPS uses sleep period time as an input to model alertness, and is often referred to as a one-step model. Other models use work hours as an input, then estimate sleep to model

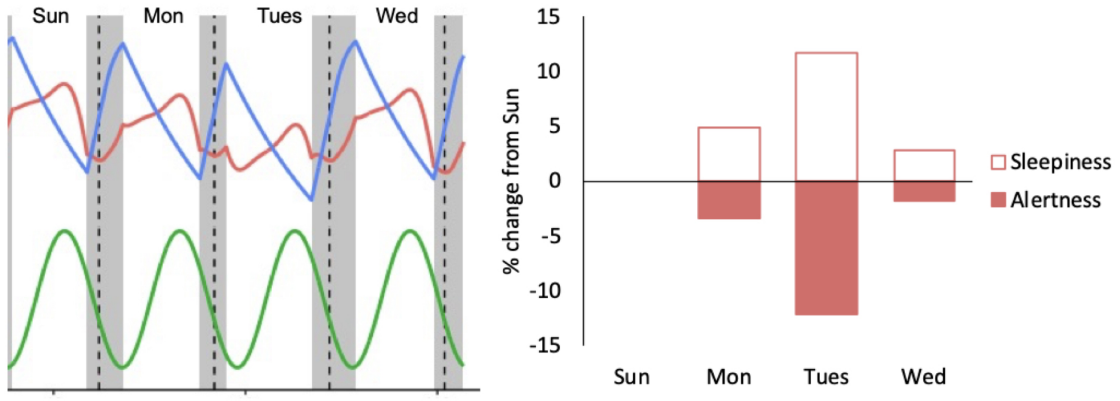


Figure 6.2: Using sleep period time to model sleepiness and alertness.

alertness. These are referred to two-step models. An advantage of the FIPS model is that the code is freely available to run in R. Other models are commercially available and have licensed user interfaces with standard reporting.

Overall, biomathematical models of alertness are often used prospectively to predict how people will function across a shift and/or across a schedule to inform roster design or schedule changes [32, 33, 34].

6.2 Patterns in Work Hours, Sleep, and Activity

We can use the actigraphy and the logbook data to examine behaviour patterns that have consequences for longer term health and safety. Examples are shown in the following sections that describe differences in behaviour at work compared to days off, and across different types of work including overnight trips and on-call.

Comparing Workdays and Days Off

Our dataset includes 221 days of logbook and actigraph data for 16 participants across metropolitan and regional depots, including 155 workdays and 66 days off. Overall, participants reported that their sleep was more disrupted than usual on 26% (40/155) of workdays. The source of the disruption was known for just under half of these occasions. One in four participants attributed their sleep disruption to an uncomfortable sleep environment, one in eight to children, and one in five to work.

Differences in actigraph estimates of sleep and physical activity are shown alongside differences in reported caffeine consumption, sleepiness, and stress, from the logbooks (Table 6.1). Average

sleep period (time from sleep onset to sleep offset) was 7.5 hours. Participants slept significantly longer on weekends, by an extra 0.4 hours on average. Time spent engaged in light physical activity was approximately 3 hours (187 mins) on workdays, and this was just under an hour less on days off (51.4 mins), which was also a statistically significant difference. Time spent in moderate and vigorous physical activity was approximately 51 minutes per workday. The difference on days off was not statistically significant. The confidence intervals for these estimates are wide, indicating large variability in the physical activity estimates. Compared to workdays, reported caffeine consumption was significantly lower on days off, as were stress ratings (Table 6.1).

Figure 6.3 shows eating pattern on workdays compared to days off. On workdays, waking occurs earlier and a larger proportion of workers eat an early meal before work. On weekends, the early morning meal is much less frequent, with eating occasions throughout the day and a larger proportion of eating at typical lunch and dinner times. On workdays, there is a higher proportion of snacks (60%) compared to days off (44%), such that participants eat more frequently on workdays. Overall, the eating window (time from first to last eating occasion) is earlier and longer on workdays.

Food timing, referred to as 'chrononutrition,' is receiving increasing attention as a research area. Studies are showing links between eating large amounts of food during the biological night, and next day metabolic consequences [37, 38, 39, 40]. Research investigating timing-based dietary strategies is providing growing evidence for the importance of understanding the ways in which work hours can influence eating patterns, which in turn, can influence health [41].

Such behavioural insights can be important, as changes in the timing and amount of sleep, physical activity, and food have been linked to risk of chronic illness including type II diabetes, gastrointestinal complaints, cardiovascular disease, and psychological illness [1, 37, 39, 40]. Behaviours change, not only in direct response to work demands, but also indirectly through strategies to cope with long and/or irregular hours. Such strategies include sleeping in on days off, use of naps, and strategies for maintaining physical activity as seen in the current dataset, and described in the interviews [42, 43].

Collection of sleep, physical activity, and diet data can assist with monitoring behaviours across different work pressures (e.g. summer heat, busy periods), and the impact of changes in work design. These data provide an understanding of context for interventions to improve health and safety.

Investigating Overnight Trips and On-Call Work

Of the 155 workdays, we captured 23 occasions where participants had an overnight sleep away from home and 9 shifts while on-call where there were call-outs. Eight of these shifts with call-outs included subsequent sleep periods for analysis (one call-out occurred on the final day of data collection for one participant). Participants reported that their sleep was more disrupted than usual on 38% (8/23) of overnight trips and 42% (3/8) of the post-call-out sleep periods. On other workdays (123), 24% were associated with sleep that was more disrupted than usual.

Comparisons between actigraph and other logbook measures for the different types of shifts relative to other workdays are shown in Table 6.2). It should be noted, that these samples,

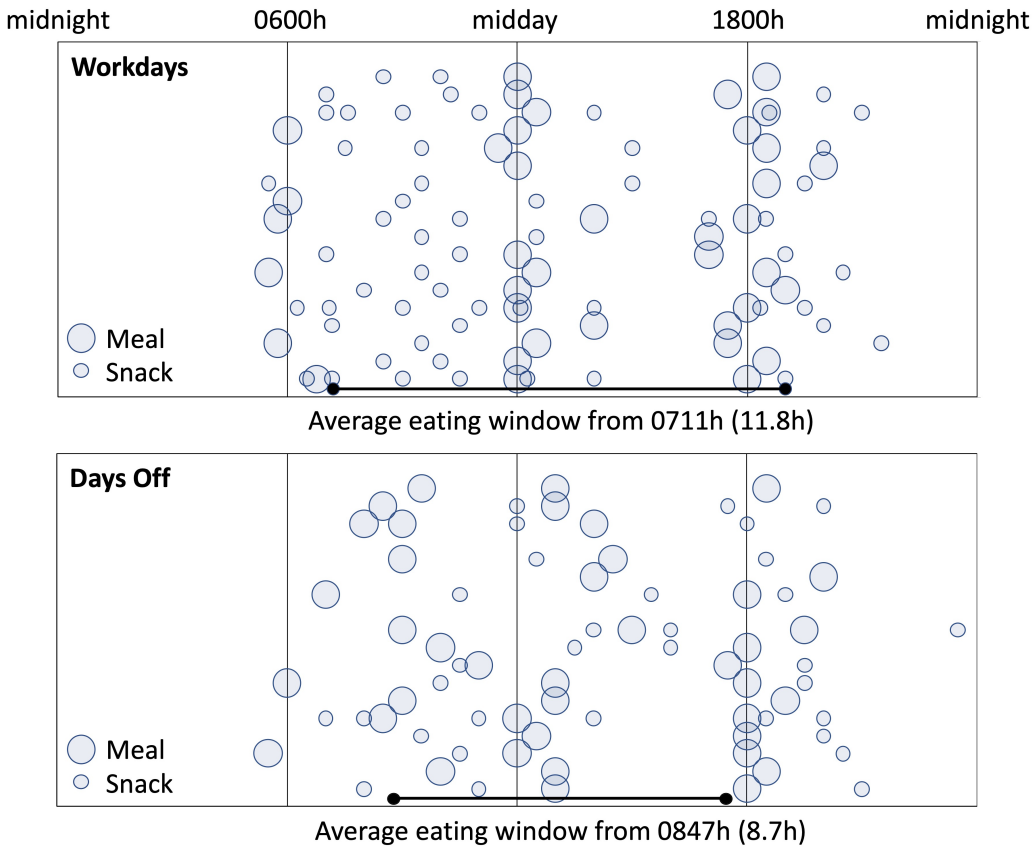


Figure 6.3: Eating patterns (timing of meals and snacks) on Workdays (upper) and Days Off (lower).

Table 6.1: Mean (95% confidence interval) values on workdays compared to days off. Bolded values show significant differences on days off compared to workdays (the 95% confidence intervals do not cross zero). *Note:* Values are estimated using linear mixed models with a fixed effect of day (workday versus day off), dependent variables of sleep, physical activity, caffeine consumption, sleepiness and stress from the actigraph and logbook, and a random effect of subject ID on the intercept to take into account within and between subject variance.

Variable	Workdays		Change on Days Off
Smartwatch			
Sleep Period (h)	7.5	+	**0.4**
	(7.0, 8.0)		**(0.1, 0.75)**
Sedentary (mins)	724.0	+	11.5
	(658.0, 790.0)		(-38.7, 61.3)
Light PA (mins)	187.0	-	**51.4**
	(151.4, 223.0)		**(-75.7, -27.1)**
MVPA (mins)	51.1	-	15.9
	(14.0, 88.2)		(-33.9, 2.0)
Logbook			
Caffeine (mg)	156.0	-	**35.2**
	(98.7, 213.0)		**(-59.1, -11.3)**
Sleepiness (20pts)	10.2	+	0.3
	(8.6, 11.8)		(-1.0, 1.5)
Stress (20pts)	8.73	-	**1.5**
	(7.2, 10.3)		**(-2.6, -0.4)**

especially for the on-call data are relatively small and as such, we are likely under-powered for statistical comparisons. The average sleep period on workdays without an overnight or a call-out was 7.6 hours. Sleep period was an average of 0.4 hours less on an overnight, and 0.3 hours less following a call out. Sedentary time was approximately 12.2 hours on workdays, and was higher on overnight trips, and lower on and after days with a call-out (significantly lower post-call-out). Light physical activity time, which was nearly 3 hours on workdays, was lower on overnights, and significantly higher on and post call-out days by more than an hour on average. Moderate to vigorous physical activity was lower on overnights, and higher on and following call-outs. Compared to other workdays, reported caffeine consumption and sleepiness were significantly higher on and post call-out days (Table 6.2).

Average shift length was 8.6 hours on workdays, and was 0.7 hours longer on overnights, 6.6 hours longer on days with a call-out (Table 6.2). Correlation analyses revealed that longer shift lengths were associated with higher ratings of sleepiness (r=0.224, p=0.006) and stress (r=0.337, p<0.001), shorter sleep periods (r=-0.297, p=0.002), and higher rates of caffeine consumption (r=0.248, p=0.002). Shorter sleep periods were also associated with higher rates of caffeine consumption (r=-0.495, p<0.001).

6.3 Key Points

Investigating sleep and activity revealed that:

- Actigraphy data was sensitive to changes in work schedules, showing differences in sleep period length and physical activity;
- Actigraphy data can feed into biomathematical models of alertness to predict levels of safety/productivity across work schedules;
- Compared to workdays, days off were associated with longer sleep periods, lower physical activity levels, lower caffeine consumption, lower stress ratings, and changes to eating patterns;
- Compared to other workdays, overnight trips and on-call days with call-outs were associated with longer work hours and increases in physical activity, sleepiness ratings, and caffeine consumption.
- Combining data with logbooks allows examination of sleep, activity, and diet, which are three of the key health pillars;
- Wrist actigraphs are relatively low burden and straightforward to use in work environments.

Table 6.2: Mean (95% confidence interval) values on other workdays compared to workdays with overnight sleep away from home (O/N), work days with call-outs after hours (call-out day), and the day following a call-out (post call-out). Bolded values show significant differences compared to other workdays (the 95% confidence intervals do not cross zero). *Note:* Values are estimated using linear mixed models with a fixed effect of day (other workdays compared to O/N, call-out days, and post call-out days), dependent variables of work hours, sleep, physical activity, caffeine consumption, sleepiness and stress from the actigraph and logbook, and a random effect of subject ID on the intercept to take into account within and between subject variance.

Variable	Workdays		Change on O/N		Change on Callout Day		Change on Post Callout
Shift length (h)	8.6	+	0.7	+	**6.6**	-	1.0
	(8.1, 9.1)		(-0.2, 1.5)		**(5.4, 7.8)**		(-2.6, 0.6)
Smartwatch							
Sleep Period (h)	7.6	-	0.4	+	0.3	-	0.3
	(7.0, 8.2)		(-1.2, 0.3)		(-0.6, 1.2)		(-1.1, 0.6)
Sedentary (mins)	729.0	+	65.6	-	89.1	-	**195.4**
	(663.0, 795.0)		(-36.9, 168.1)		(-226.6, 48.4)		**(-324.1, -66.8)**
Light PA (mins)	174.0	+	4.4	+	**94.3**	+	**89.6**
	(136.0, 213.0)		(-46.7, 55.5)		**(29.3, 159.3)**		**(28.8, 150.4)**
MVPA (mins)	48.3	-	22.2	+	35.7	+	45.7
	(15.1, 81.5)		(-62.4, 18.1)		(-14.9, 86.3)		(-1.7, 93.1)
Logbook							
Caffeine (mg)	139.0	+	18.9	+	**81.4**	+	**19.3**
	(76.9, 202.0)		(-26.8, 64.5)		**(21.8, 141.1)**		**(15.5, 143.1)**
Sleepiness (20pts)	9.3	+	1.7	+	**3.3**	+	**5.1**
	(7.6, 11.0)		(-0.5, 3.8)		**(0.5, 6.1)**		**(2.1, 8.1)**
Stress (20pts)	8.1	+	1.2	+	2.0	+	2.1
	(6.6, 9.6)		(-0.7, 3.1)		(-0.5, 4.6)		(-0.6, 4.8)

7. Pressure Sensors and Gait

SMART insoles contain a series of sensors that measure pressure and acceleration to monitor changes in gait. The Moticon insoles used in this study use 16 sensors across the foot, covering toe, metatarsal head, arch, and heel sections. Each sensor records a signal at sampling rate of 10 Hz. Sensor signals can be analysed individually or in aggregate. Insole data has been shown to be valid for measuring gait indicators [44, 45], jumps and balance [46], slips, trips, and loss of balance [47], and safety hazards [48].

Service Laying

Insole data collected over 32 minutes during a service laying is shown in Figure 7.1. The upper panel shows total pressure on the left and right foot during 17 seconds of walking at the beginning of the service laying. Relatively even pressure transfer from left to right foot and back can be seen across the recording period. If we examine the data across the full 32 minute task (lower panel) we can see the total pressure changes (shown for the right foot) associated with walking, standing, and sitting.

Meter Reading

Insole data collected over a 2.5-hour period of meter reading is shown in Figure 7.2. The pattern here is different to the service laying in that periods of standing, walking, squatting, and bending are punctuated by periods of sitting in the car, travelling between meters.

Notes on Analysis and Next Steps

A key element that facilitates data analysis and interpretation of changes in individual movements is simultaneous video recording. This allows data to be categorised into movement types, and then analysis can examine changes in pressure across time, or in response to environmental factors, within specific repeated movement patterns, such as walking or squatting. We have concomitant video for the meter reading, and still images for service laying.

Once a dataset of sufficient size is collected, machine learning techniques can be applied to

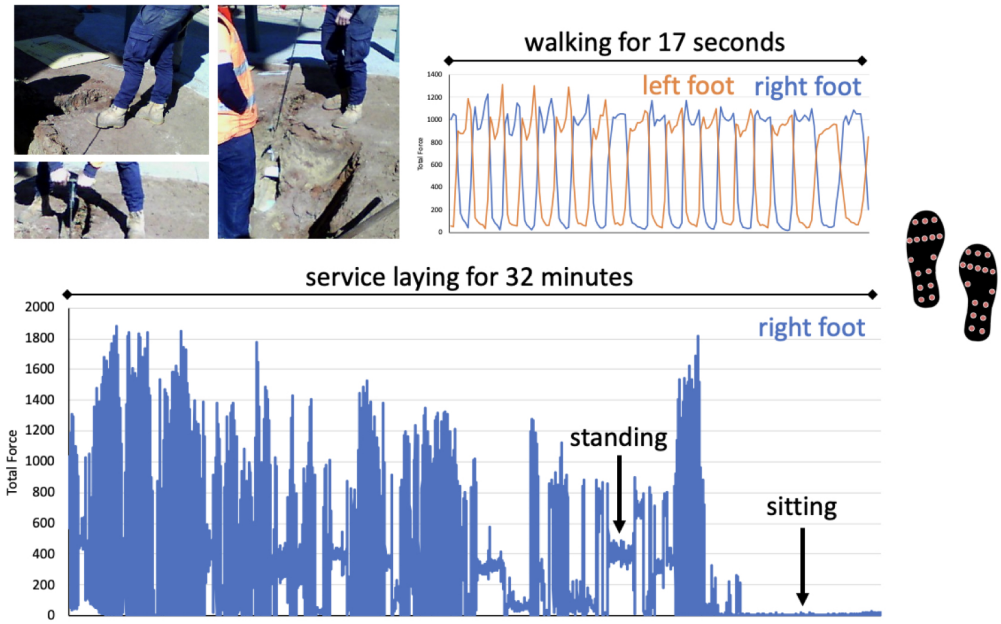


Figure 7.1: Insole data during service laying.

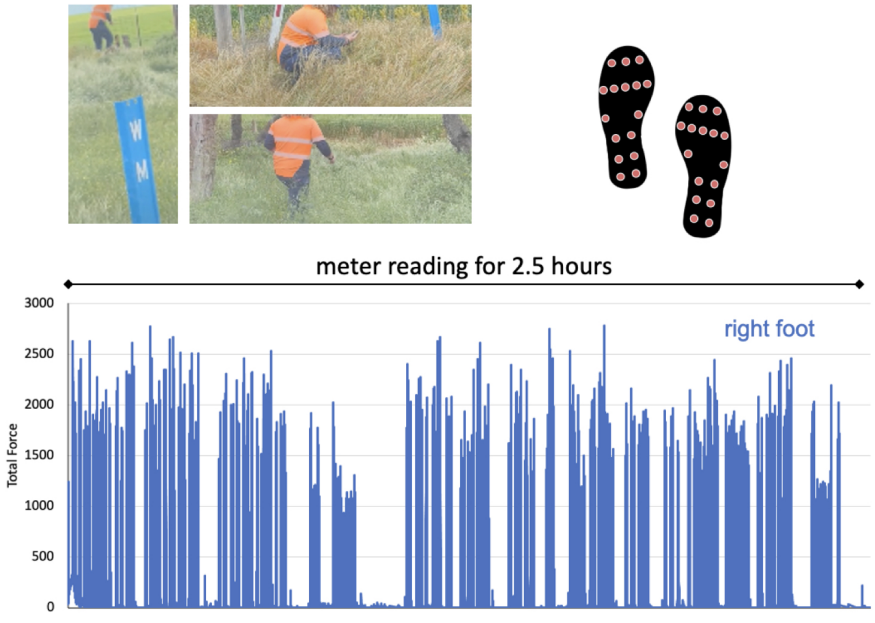


Figure 7.2: Insole data during meter reading.

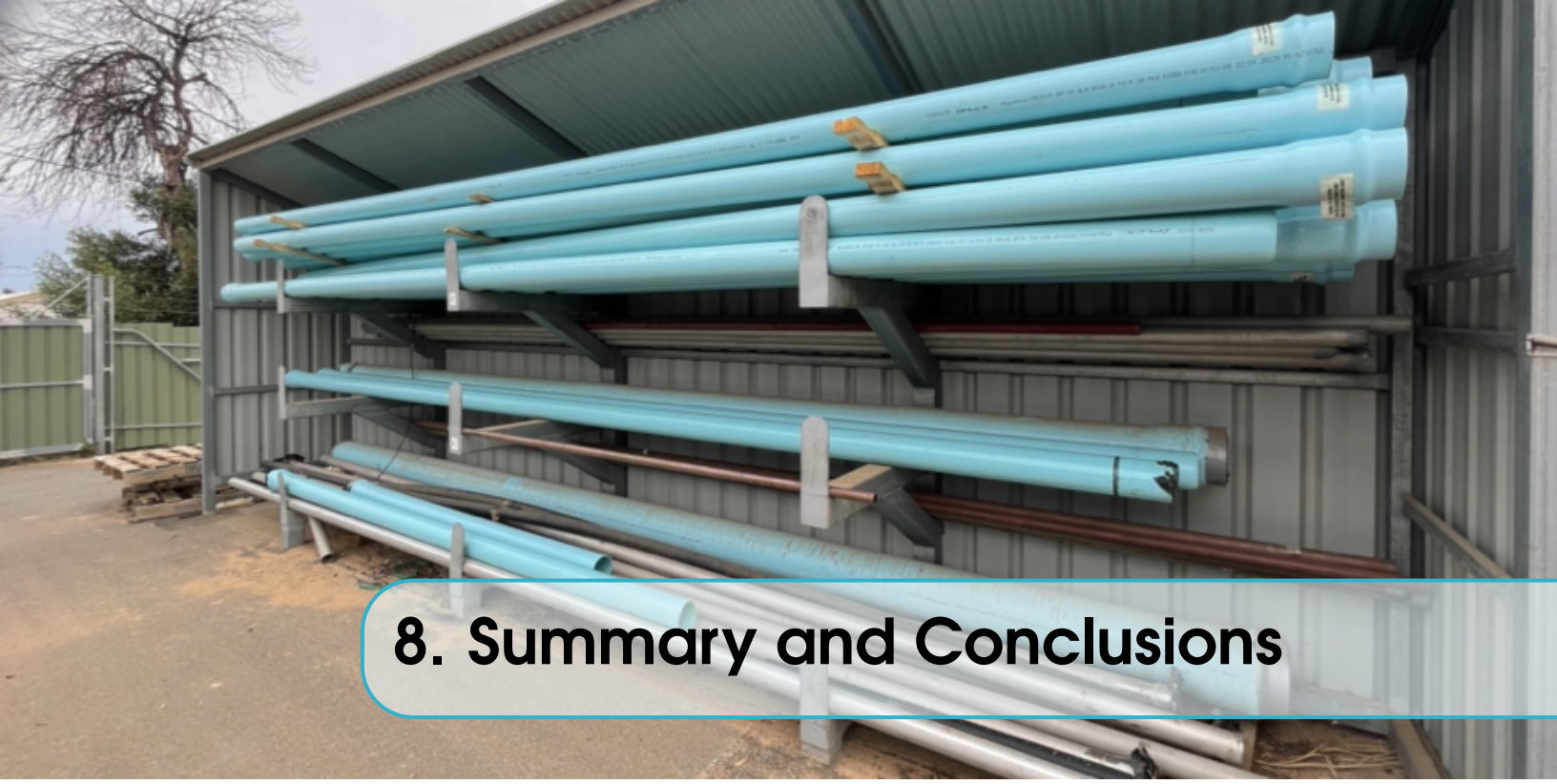
automatically detect movement patterns (e.g. walking) and characteristics (e.g. slips, trips, falls) for analysis [49, 50]. Research has shown that, for example, the patterns in plantar pressure in the heel are particularly useful for identifying slips [51, 52].

In the absence of a dataset large enough to facilitate this level of automation, manual analysis can be conducted. It would be interesting to re-run insole data collection during meter reading during hot weather and/or during busy periods (e.g. following on-call activity). The current dataset would provide a baseline comparison to ask questions such as 'Does peak pressure in the heel vary during tasks (walking, squatting, climbing into/out of trenches) across the workday and with heat and increased workload?'

7.1 Key Points

Using smart insoles to measure gait revealed that:

- Smart insoles were sensitive to differences in activities, including walking, standing, and sitting;
- Pressure patterns also show differences in work types including differences between service laying and meter reading;
- Insoles are not straightforward to use in the field as they require concurrent video (until the dataset is sufficiently large to develop machine learning techniques to identify movement types), and since data recording can drop out and the insoles cannot be immersed in water or used while driving. Further research could include newer products that do not have the same limitations and are more suitable for work conditions;
- Further data collection in summer would allow examination of gait changes across shifts in relation to work intensity and weather.



8. Summary and Conclusions

8.1 Findings Summary

Interviews identified heat, fatigue, and driving as key WHS focus areas. The devices were used to successfully capture related data in the field (summarised in Figure 8.1), specifically:

- Wrist actigraph data were used to model sleep, physical activity, alertness, and sleepiness, showing sensitivity to varying work tasks, with relatively high usability and a moderate degree of data processing.
- Smart shirt data were used to model exertion and activity levels, showing sensitivity to actual and simulated work relative to thermal conditions. Usability was somewhat limited by requirements to reapply electrode gel. A moderate level of data processing and modelling was required.
- Smart insoles were used in the field to detect differences in activities. With supplementary data collection and application of further, more in-depth analysis, sensors could be used to explore changes in gait (e.g. slips, balance changes) across shifts in relation to work intensity and ambient conditions. Usability is limited by connectivity requirements and the unsuitability of the insoles for certain tasks (involving wet feet or driving).

Synthesising wearable data with logbook, IVSS, and environmental measures provided the necessary context to categorise, analyse and interpret the data. Modelling approaches were useful in transforming the output signals into easily interpretable metrics. The main findings from each chapter are summarised in Table 8.1.

8.2 Discussion and Next Steps

As with fatigue, heat exposure is a recognised work health and safety hazard [53, 54]. Further, heat exacerbates the negative effects of fatigue [34]. Heat exposure that exceeds the body's ability to maintain body temperature can result in dehydration, exhaustion, cramps, fainting,

Table 8.1: Findings summary.

Thermal imaging of skin and micro-environments revealed that:	▪ Changes in skin temperature were sensitive to changes in work environments and tasks ▪ The mock trial provided a platform for investigating differences in ambient temperature, task length, and PPE ▪ Results support the thermal benefits of PAPR and ice vests
Modelling **thermal comfort** in winter and summer revealed that:	▪ Conditions during the winter pipe removal trial resulted in modelled thermal comfort levels that were within the recommended range. However, summer conditions were well outside comfort zones ▪ Models were supported by thermal sensation and comfort ratings ▪ PAPR and ice vests are likely to provide some beneficial recovery for thermal comfort
Modelling **exertion using heart rate (HR)** revealed that:	▪ HR collected using smart shirts was sensitive to differences in task and sleep/wake status ▪ HR data supported thermal comfort and thermal imaging findings regarding the discomfort experienced during summer heat with full asbestos PPE ▪ Findings suggest that working under these conditions may result in physical exertion at high levels of intensity ▪ Findings also support the use of PAPR and ice vests to attenuate heat stress
Investigating **sleep and activity** revealed that:	▪ Actigraphy data were sensitive to changes in work schedules, showing differences in sleep period length and physical activity ▪ Compared to workdays, days off were associated with longer sleep periods, lower physical activity levels, lower caffeine consumption, lower stress ratings, and changes to eating patterns ▪ Compared to other workdays, overnight trips and on-call days with call-outs were associated with longer work hours and increases in physical activity, sleepiness ratings, and caffeine consumption
Using **smart insoles to measure gait** revealed that:	▪ Smart insoles were sensitive to differences in activities, including walking, standing, and sitting ▪ Pressure patterns also show differences in work types including differences between service laying and meter reading

and heat stroke. Understanding the impacts of heat can assist with safe work design [54]. Examples of hazard management include rescheduling work to a cooler time, monitoring symptoms, training for identification of heat symptoms, potable water, cooling vests, and access to air-conditioned environments. Different countries and jurisdictions have different methods for estimating reasonable heat exposure limits, including suggested work/rest schedules based on temperature, activity, and clothing (e.g. PPE) [53]. Further data collection in the heat could assist with understanding exposure in Australian conditions. In considering further heat and fatigue research in this cohort, the addition of a core body temperature (CBT) measure would be advantageous. Not only is CBT a key indicator of heat stress, it is also an indicator of circadian timing. Combined with HR/exertion and thermal comfort analysis, CBT can provide information about heat stress [53]. Measurement has become more straightforward through use of pills that measure temperature as they travel through the intestine [55].

> "Physiologic monitoring, such as heart rate and/or core temperature, of heat-exposure workers could help protect all workers" (NIOSH, 2016, p99 [53])

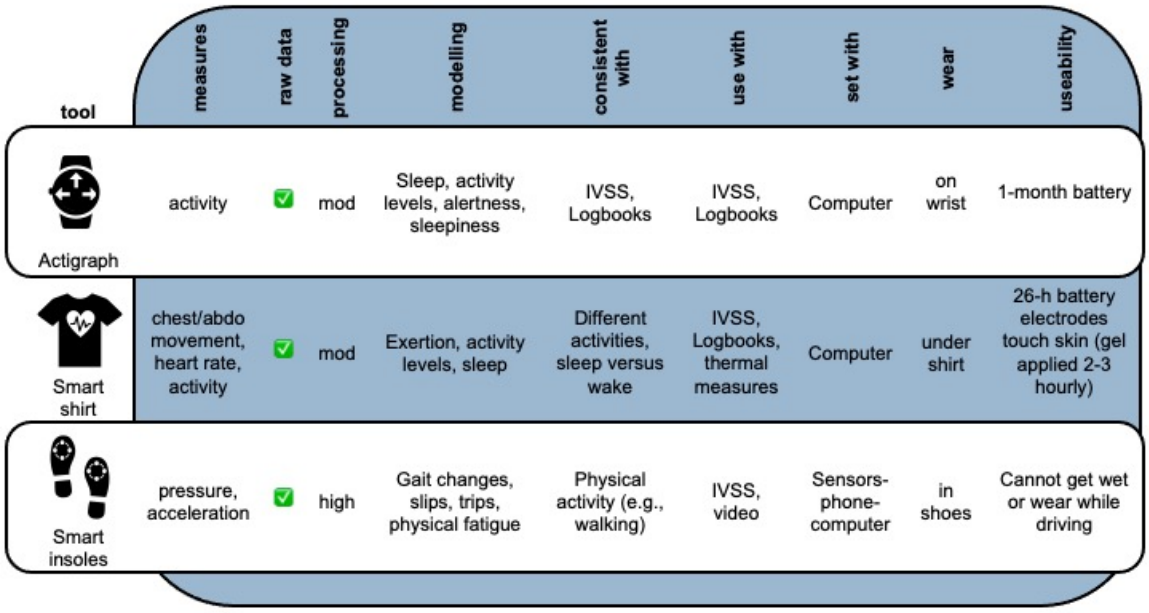
Further, the insoles were not straightforward to use in the field as they require concurrent video (until the dataset is sufficiently large to develop machine learning techniques to identify movement types). There was also data recording drop-out. Perhaps most importantly, these insoles could not be immersed in water or used while driving. Since the time of initiating this research, new insoles have become available that are fit for wet environments, with technology that has developed in many ways. Trialling some of these new insoles could enable collection of larger amounts of data while driving and engaging in activities where workers may get wet.

Overall, findings suggest that next steps could include:

- Further research to examine findings in a larger sample and to differentiate the impact of time-on-task and PPE;
- More in-depth study of PPE combinations using HR monitoring, in combination with other thermal measures such as core body temperature;
- Comparing differences in exertion for different task types (e.g., driving, water testing, meter reading, pipe repair);
- Further data collection with new insoles to examine gait changes across shifts in relation to work intensity and weather.
- SA Water could consider purchasing some equipment in order to collect data more frequently and for longer periods. This would facilitate more in-depth analysis of key circumstances (e.g., emergencies, large periods on-call, periods of staff absence, etc.), to more powerfully capture non-frequent stress points as well as normal running.

8.3 Conclusions

Findings reinforce the use of wearable sensors in operational settings as part of an ecosystem of measurements, conducted across varying conditions to establish sensitivity and usability. Data can then be modelled using standard algorithms to aid in translation and application (Figure 8.1).



tool	measures	raw data	processing	modelling	consistent with	use with	set with	wear	useability
Actigraph	activity	☑	mod	Sleep, activity levels, alertness, sleepiness	IVSS, Logbooks	IVSS, Logbooks	Computer	on wrist	1-month battery
Smart shirt	chest/abdo movement, heart rate, activity	☑	mod	Exertion, activity levels, sleep	Different activities, sleep versus wake	IVSS, Logbooks, thermal measures	Computer	under shirt	26-h battery electrodes touch skin (gel applied 2-3 hourly)
Smart insoles	pressure, acceleration	☑	high	Gait changes, slips, trips, physical fatigue	Physical activity (e.g., walking)	IVSS, video	Sensors-phone-computer	in shoes	Cannot get wet or wear while driving

Figure 8.1: Summary of what each wearable device measured, whether raw data was accessible (tick=yes), level of processing required from the raw data (low, mod=moderate, high), algorithms and modelling that can be used to interpret the data, which measures the wearable data were consistent with (showing expected variation as a function of activity level and work task), which measures were used together with each wearable to understand the data in context, the tools required to set and download the wearables, how they were worn, and a description of their usability.

Overall, using this ecosystem:

- Wearable sensors can be 'operationalised' across these work crews to provide objective indicators of heat and fatigue. Alongside self-perception, this information could support fitness-for-work decisions.
- 'Workplace monitoring kits,' can be created to provide insights during periodic monitoring of hazardous tasks. Using sensor data to model heat and other physiological stressors would allow quantification of the effect of different work practices to optimise procedures, equipment procurement, and rostering.

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