# Advancing the Measurement and Understanding of Composite Sleep Health in Shift-Working Populations

Geoff Passfield

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| **Student Name:** Geoff Passfield | **Signature:** **Date:** **31/07/26** |

# Co-Authorship Contribution

**STUDENT AND SUPERVISOR APPROVALS**

***By signing you are confirming that the co-author contributions stated in the table(s) below are accurate.***

| | | | | | |
|---|---|---|---|---|---|
| **Student Name** | Geoff Passfield | **Signature** | | **Date** | 31/07/26 |
| **Supervisor Name** | Tom Stewart | **Signature** | | **Date** | 31/07/26 |

| | |
|---|---|
| **Chapter Number:** | 3 |
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| **AUTHOR SURNAME:** | **CONTRIBUTION** |
|---|---|
| **Passfield** | Conception and design of project, investigation, data collection, methodology, formal analysis, visualisation, writing – original draft, writing – review and editing, project administration. |
| **Stewart** | Conception, data processing, resources, writing – review and editing, supervision. |
| **Mackay** | Conception, methodology, writing – review and editing, supervision. |
| **Crofts** | Methodology, writing – review and editing, formal analysis, supervision. |
| **Schofield** | Supervision. |

| | |
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| AUTHOR SURNAME: | CONTRIBUTION |
|---|---|
| **Passfield** | Conception and design of the project or output;<br>Acquisition of research data where the acquisition has required significant intellectual judgement, planning, design, or input;<br>Contribution of knowledge, where justified, including Indigenous knowledge;<br>Analysis or interpretation of research data;<br>Drafting significant parts of the research output or critically revising it so as to contribute to its quality and interpretation. |
| **Mackay** | Conception and design of the project or output;<br>Acquisition of research data where the acquisition has required significant intellectual judgement, planning, design, or input;<br>Contribution of knowledge, where justified, including Indigenous knowledge;<br>Analysis or interpretation of research data;<br>Drafting significant parts of the research output or critically revising it so as to contribute to its quality and interpretation. |
| **Stewart** | Contribution of knowledge, where justified, including Indigenous knowledge;<br>Analysis or interpretation of research data;<br>Drafting significant parts of the research output or critically revising it so as to contribute to its quality and interpretation. |
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| **Mackay** | Conception and design of the project or output; |
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| **Stewart** | Contribution of knowledge, where justified, including Indigenous knowledge;<br>Analysis or interpretation of research data;<br>Drafting significant parts of the research output or critically revising it so as to contribute to its quality and interpretation. |
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| **Mackay** | Conception and design of the project or output. |

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# Thesis Abstract

**Introduction:** Sleep is a fundamental biological process that supports mental and physical functioning. Its restorative value depends not only on sufficient duration, but also on sleep being consolidated, efficient, regular, and timed appropriately within environmental and physiological rhythms. These dimensions can be understood through the framework of sleep health, which conceptualises sleep as a multidimensional construct. This framework is particularly relevant for shift-workers, whose work schedules can disrupt circadian alignment, constrain sleep opportunity, and alter the distribution of behaviours across the 24-hour day. However, existing research has tended to examine individual sleep metrics or subjective sleep outcomes, with limited attention to objectively measured sleep health in real-world shift-working populations. This thesis investigated the measurement, distribution, and behavioural context of objectively measured composite sleep health (CSH) in shift-workers.

**Methods:** This thesis comprised five interconnected studies using accelerometery and diary data from free-living adult workers. An initial agreement study compared sleep metrics derived from wrist, mid-thigh, and low-back accelerometers. Subsequent studies applied a five-dimension CSH framework, comprising duration, variability, efficiency, timing, and regularity, to examine differences across work-pattern groups, associations with self-reported health and well-being outcomes, relationships with health behaviours, and associations with 24-hour time-use composition.

**Results:** Mid-thigh accelerometery produced sleep estimates broadly comparable to wrist-derived estimates, supporting its use for group-level CSH assessment. Objectively measured CSH was generally poor across the cohort, with night shift-workers showing the poorest multidimensional sleep health. CSH showed limited associations with self-reported psychosocial and health outcomes, although subjective sleeping troubles showed the clearest relationship. Most self-reported health behaviours explained little variance in CSH. The 24-hour time-use profile of shift-workers was dominated by sedentary time, followed by sleep, with smaller proportions of the day spent in light and moderate-to-vigorous physical activity. In compositional analyses, greater relative

sedentary time was associated with lower CSH, while greater relative sleep was associated with higher CSH.

Conclusions: Objective CSH provides a practical framework for multidimensional sleep health, moving beyond single sleep metrics to show how sleep duration, variability, efficiency, timing, and regularity combine within real-world working conditions. By linking objectively measured sleep health with work-pattern differences, self-reported health outcomes, health behaviours, and 24-hour time use, this thesis demonstrates that poor sleep health in shift-workers is not simply a sleep-duration problem, but part of a broader behavioural and occupational context. These findings support the value of objective, multidimensional sleep assessment for identifying sleep-health burden in shift-working populations and for informing future research focused on feasible, context-sensitive strategies to improve sleep health.

# Table of Contents

Attestation of Authorship ..... i
AI Disclosure Statement ..... i
Co-Authorship Contribution ..... ii
Acknowledgements ..... vi
Thesis Abstract ..... vii
Table of Figures ..... xi
Table of Tables ..... xi
Chapter 1 – Introduction ..... 1
Background ..... 1
Thesis rationale ..... 3
Thesis organisation ..... 5
Chapter 2 – Literature Review ..... 8
Introduction ..... 8
Sleep Architecture and Regulation ..... 9
Sleep Disruption, Health, and Population Variability ..... 11
Sleep Health as a Multidimensional Construct ..... 12
Sleep Health Data Collection ..... 23
Sleep, Time-use, and Health Behaviours ..... 30
Composite Sleep Health in Shift-Working Populations ..... 38
Research Gaps ..... 44
Summary ..... 45
Chapter 3 – Agreement Between Wrist, Thigh, and Low-Back Accelerometery Using a Wrist-Based Algorithm ..... 47
Prelude ..... 47
Abstract ..... 48
Introduction ..... 49
Methods ..... 51
Results ..... 55
Discussion ..... 61
Chapter 4 – Differences in Composite Sleep Health Between Shift and Non-Shift-Workers ..... 65
Prelude ..... 65
Abstract ..... 66
Introduction ..... 67
Methods ..... 68
Results ..... 75
Discussion ..... 81
Chapter 5 – The Association Between Composite Sleep Health and Health and Well-being Outcomes in Shift-Workers ..... 86
Prelude ..... 86
Abstract ..... 87
Introduction ..... 89
Methods ..... 91
Results ..... 94

Discussion ..... 98
Chapter 6 – The Association Between Composite Sleep Health and Health Behaviours in Shift-Workers ..... 102
Prelude ..... 102
Abstract ..... 103
Introduction ..... 105
Methods ..... 106
Results ..... 111
Discussion ..... 115
Chapter 7 – The Association Between Composite Sleep Health and 24-Hour Time-Use Behaviour in Shift-Workers ..... 119
Prelude ..... 119
Abstract ..... 120
Introduction ..... 122
Methods ..... 123
Results ..... 127
Discussion ..... 133
Chapter 8 – General Discussion ..... 137
Research summary ..... 137
Significance of findings ..... 139
References ..... 150
Appendices ..... 168
Appendix A – Supplementary Material for Chapter 3 ..... 168
Appendix B – Supplementary Material for Chapter 5 ..... 175
Appendix C – Supplementary Material for Chapter 7 ..... 176
Appendix D – Participant sampling schematic across Chapters 4–7 ..... 188
Appendix E – Ethical Approval Letters ..... 189

# Table of Figures

Figure 1-1. Thesis structure and flow of chapters ..... 7
Figure 3-1. Placement Locations of Accelerometer Devices ..... 52
Figure 3-2. Example of Minute-by-Minute Sleep Data From a Single Participant ..... 56
Figure 3-3. Confusion Matrices for Mid-thigh and Low-back Devices ..... 57
Figure 3-4. Bland Altman Plot for TST ..... 60
Figure 7-1. Proportional Reallocations (one-versus-many) ..... 131
Figure 7-2. One-versus-One Reallocations ..... 132

Appendix Figure 1. Visual Discrepancy Outliers ..... 168

# Table of Tables

Table 3-1. Descriptive statistics for a range of sleep metrics for each device location ..... 55
Table 3-2. Disagreement bouts: mid-thigh and low-back versus wrist ..... 57
Table 3-3. Repeated measures ANOVA results for each sleep metric ..... 58
Table 3-4. Post hoc contrasts across metrics ..... 59
Table 4-1. Composite Sleep Health dimensions, metrics, thresholds, and rationales ..... 74
Table 4-2. Participant Characteristics ..... 76
Table 4-3. Sleep Dimension Means and Standard Deviations ..... 77
Table 4-4. Distribution of Sleep Dimension Scores Across Shift Groups ..... 78
Table 4-5. Median (IQR) composite sleep health dimension scores by work-pattern group ..... 79
Table 4-6. Bonferroni-adjusted post-hoc pairwise comparisons for individual sleep dimensions ..... 81
Table 5-1. Demographic characteristics of the sample ..... 95
Table 5-2. Descriptive statistics for composite sleep health and well-being measures (n = 88) ..... 96
Table 5-3. Linear regression results (n = 88) ..... 97
Table 6-1. Demographic characteristics ..... 111
Table 6-2. Unadjusted linear regression models ..... 112

Table 6-3. Adjusted models for Gender, Age, and BMI ..... 114
Table 7-1. Sequential Binary Partition Structure Used to Generate ILR Coordinates ..... 126
Table 7-2. Participant Characteristics, Wear Compliance, and CSH ..... 128
Table 7-3. Mean and Percentage of Time Spent in Each Activity Type per Day ..... 129
Table 7-4. Relationship Between Activity Intensity Compositions (Expressed as Isometric log-ratio Coordinates) and CSH ..... 130

Appendix Table 1. Configuration Settings Used for Accelerometer Data Processing ..... 169
Appendix Table 2. Bland Altman and Pearson Correlation Values, Mid-thigh Compared to Wrist ..... 174
Appendix Table 3. Bland Altman and Pearson Correlation Values, Low-back Compared to Wrist ..... 174
Appendix Table 4. Unadjusted Model of Shift-workers With More Than 1 Night of Sleep Data ..... 175
Appendix Table 5. Configuration Settings Used for Accelerometer Data Processing ..... 176
Appendix Table 6. Relationship Between Activity Compositions (with sleep removed) and CSH ..... 183
Appendix Table 7. Isotemporal Substitution Estimates for Reallocations Around the Sample Composition ..... 184
Appendix Table 8. One-versus-one Isotemporal Substitution Estimates for Reallocations Around the Sample Composition ..... 185

## List of acronyms

ANOVA- Analysis of variance

AWK- Awakenings

BMI- Body mass index

BRS- Brief Resilience Scale

CI- Confidence interval

CoDA- Compositional data analysis

COPSOQ II- Copenhagen Psychosocial Questionnaire II

CSH- Composite sleep health

CV- Coefficient of variation

IQR- Interquartile range

LPA- Light physical activity

MELAA- Middle Eastern, Latin American, and African

MET- Metabolic equivalent

MPA- Moderate physical activity

MVPA- Moderate-to-vigorous physical activity

PA- Physical activity

PDD- Personal day dominant

SD- Standard deviation

SE- Sleep efficiency

SHI- Sleep health index

SI- Sleep interval

SOT- Sleep onset timestamp

TST- Total sleep time

VPA- Vigorous physical activity

WASO- Wake after sleep onset

# Chapter 1 – Introduction

## Background

Sleep is a fundamental biological process that plays a critical role in maintaining physical, cognitive, and emotional health. Adequate sleep supports homeostatic regulation, cognitive performance, and psychological well-being, while insufficient or poor-quality sleep is associated with a wide range of adverse outcomes, including cardiovascular disease, metabolic dysfunction, and mental health disorders (Hillman & Lack, 2013; Lim & Dinges, 2010).

In recent years, sleep has increasingly been conceptualised as a multidimensional construct, often referred to as *sleep health* (Buysse, 2014; Lee & Lawson, 2021). This framework recognises that sleep cannot be adequately described by a single metric such as duration alone, but instead comprises multiple interrelated dimensions, including duration, efficiency, timing, regularity, satisfaction, and daytime alertness. These dimensions interact to influence overall functioning, and composite sleep health (CSH) metrics have been shown to provide a more comprehensive and predictive assessment of health outcomes than single-variable measures.

Sleep is also embedded within the broader 24-hour behavioural cycle. Daily time is distributed across sleep, sedentary behaviour, light physical activity, and moderate-to-vigorous physical activity, which are inherently interdependent (Dumuid et al., 2020). Changes in one behaviour necessarily influence the others, meaning that sleep must be understood within the context of overall time use. This compositional perspective has gained increasing attention, with evidence suggesting that the distribution of daily behaviours influences multiple dimensions of sleep health.

Accurate measurement of sleep in free-living environments remains a critical challenge. While polysomnography provides detailed physiological data, its laboratory-based nature makes it less suited to repeated assessment of sleep under everyday living conditions (Ancoli-Israel et al., 2015; Matsuo et al., 2016). Self-reported measures are widely used,

but comparisons with actigraphy show that reported sleep duration can differ substantially from objectively estimated sleep duration (Cespedes et al., 2016; Lauderdale et al., 2008). Wearable accelerometers have emerged as a practical and scalable solution, enabling objective, continuous monitoring of sleep and waking behaviours in real-world settings. However, methodological challenges remain, including the influence of device placement on measurement accuracy and the limited availability of validated approaches capable of simultaneously capturing sleep, physical activity, and sedentary behaviour using a single device (Crowley et al., 2019; Johansson et al., 2023).

These challenges are particularly relevant in shift-working populations. Shift-work, defined as employment occurring outside traditional daytime hours, is a common feature of modern economies and affects a substantial proportion of the workforce (Silva et al., 2020). In New Zealand, Stats NZ reported that two-thirds of employed people had worked at a non-standard time at least once in the previous four weeks, while 12% had worked at night between 11 p.m. and 5 a.m. (Stats NZ, 2019). Such schedules disrupt circadian rhythms, resulting in insufficient sleep, irregular sleep timing, and reduced sleep quality. These disruptions are associated with increased risks of chronic disease, impaired cognitive performance, and poorer psychological well-being (Knutsson, 2003; Wu et al., 2022).

Despite the well-established impact of shift-work on sleep, much of the existing research relies on single sleep metrics or subjective measures, limiting understanding of how multidimensional sleep health is affected. Furthermore, relatively little research has examined how composite sleep health varies across different shift schedules, how it relates to health and well-being outcomes, or how it is influenced by modifiable behaviours and 24-hour time-use patterns. These gaps highlight the need for comprehensive, objectively measured approaches to understanding sleep health in shift-working populations.

## Thesis rationale

The emerging concept of composite sleep health provides a framework for understanding sleep as a multidimensional and behaviourally embedded process (Buysse, 2014; Dumuid et al., 2020). However, its application within shift-working populations remains limited, particularly when using objective measurement approaches in free-living environments. Addressing this gap requires a programme of research that spans methodological validation, population-level description, and behavioural and health-related correlates.

A key methodological challenge lies in the ability to accurately and efficiently measure sleep alongside other daily behaviours. While wrist-worn accelerometers are widely used for sleep assessment (van Hees et al., 2015), they have limitations in distinguishing postural behaviours (Montoye et al., 2016; Suorsa et al., 2020). Alternative placements, such as thigh-mounted devices, may offer improved classification of sedentary behaviour while also providing viable sleep metrics, though evidence supporting their use remains limited.

Beyond measurement, there is a need to better understand how composite sleep health varies across different types of shift-work. Existing research has often focused on healthcare populations (Furihata et al., 2020; Giorgi et al., 2018; Hulsegge et al., 2019), with limited evidence from other industries such as transportation and logistics, and little representation from the New Zealand context. Furthermore, the extent to which multidimensional sleep health relates to psychosocial outcomes, lifestyle behaviours, and the distribution of time across the 24-hour day remains underexplored.

Collectively, these gaps highlight the need for an integrated approach that considers sleep health as part of a broader behavioural system, measured objectively and examined within populations most vulnerable to sleep disruption.

## Statement of the purpose

The overall purpose of this thesis is to investigate objectively measured composite sleep health in shift-working populations, with a focus on its measurement, distribution, and associations with health outcomes and daily behaviours.

To achieve this, the thesis addresses the following specific aims:

1. To evaluate the agreement between accelerometer placements (wrist, mid-thigh, and lower back) for estimating sleep metrics, and to assess the feasibility of a single-device approach for integrated 24-hour behaviour measurement (Chapter 3).
2. To determine whether composite sleep health differs across work schedules, including different types of shift-work, and to identify which dimensions of sleep health contribute to these differences (Chapter 4).
3. To examine the association between composite sleep health and health and well-being outcomes, including stress, burnout, resilience, depression, and sleep-related difficulties (Chapter 5).
4. To investigate the extent to which modifiable lifestyle behaviours (e.g., physical activity, diet, caffeine and alcohol consumption, smoking, and use of sleep aids) explain variation in composite sleep health among shift-workers (Chapter 6).
5. To examine how the composition of 24-hour time use is associated with composite sleep health, and to estimate the predicted effects of reallocating time between behaviours on sleep health outcomes (Chapter 7).

Together, these aims form a coherent programme of research that progresses from methodological validation to applied behavioural and epidemiological analyses, providing a comprehensive understanding of composite sleep health in shift-working populations.

# Thesis organisation

## Thesis context

The work presented in this thesis is embedded within a larger research programme examining job demands and recovery from work among employees of Air New Zealand. This parent project was conducted by researchers at Auckland University of Technology's Human Potential Centre and aimed to characterise the physical, cognitive, and emotional demands experienced by workers across the full 24-hour day, both within and outside of occupational settings.

The Air New Zealand study employed a comprehensive, multi-method design in a free-living environment. Two phases of data collection were completed over the duration of the study: an initial pilot, and a revised more comprehensive collection of subjective survey data. Across both phases, participants were asked to wear two accelerometers, positioned at the mid-thigh and lower back, continuously for seven days. This enabled objective measurement of posture, movement, and sleep-related behaviours. In addition to accelerometery, participants in both phases were asked to maintain an activity/work/sleep diary. Phase 1 participants completed a demographic survey, while Phase 2 participants completed an expanded survey battery that included additional self-reported health, psychosocial, and lifestyle behaviour measures, as well as job and job-related characteristics data. Additionally, Phase 2 participants were asked to respond to repeated ecological momentary assessment prompts via text message to capture real-time fatigue and recovery states.

The present thesis utilises data derived from this broader study, with a specific focus on the objective assessment of sleep and its role within the 24-hour behavioural cycle. While the original study was designed to investigate job demands and recovery, it did not explicitly examine sleep through a multidimensional or composite sleep health framework. This thesis extends the scope of the parent project by applying contemporary sleep health models to objectively measured data, enabling a more comprehensive evaluation of sleep in a shift-working population.

## Thesis structure

This thesis is presented as a series of interconnected studies that collectively examine the measurement, distribution, and behavioural context of composite sleep health in shift-working populations. It includes distinct publications adapted into chapter format (see Figure 1-1). Chapter 2 provides a narrative literature review, outlining the theoretical and empirical foundations of sleep health, accelerometery-based measurement, shift-work, and 24-hour time-use frameworks. Chapter 3 evaluates the agreement between accelerometer placements for measuring sleep, establishing the methodological foundation for the thesis. Chapter 4 compares composite sleep health across different work schedules. Chapter 5 examines associations between composite sleep health and psychosocial health outcomes. Chapter 6 investigates the relationships between lifestyle behaviours and composite sleep health. Chapter 7 explores the association between 24-hour time-use composition and composite sleep health, including time reallocation analyses. Finally, Chapter 8 provides an overall discussion, synthesising findings across studies, outlining theoretical and practical implications, and identifying directions for future research.

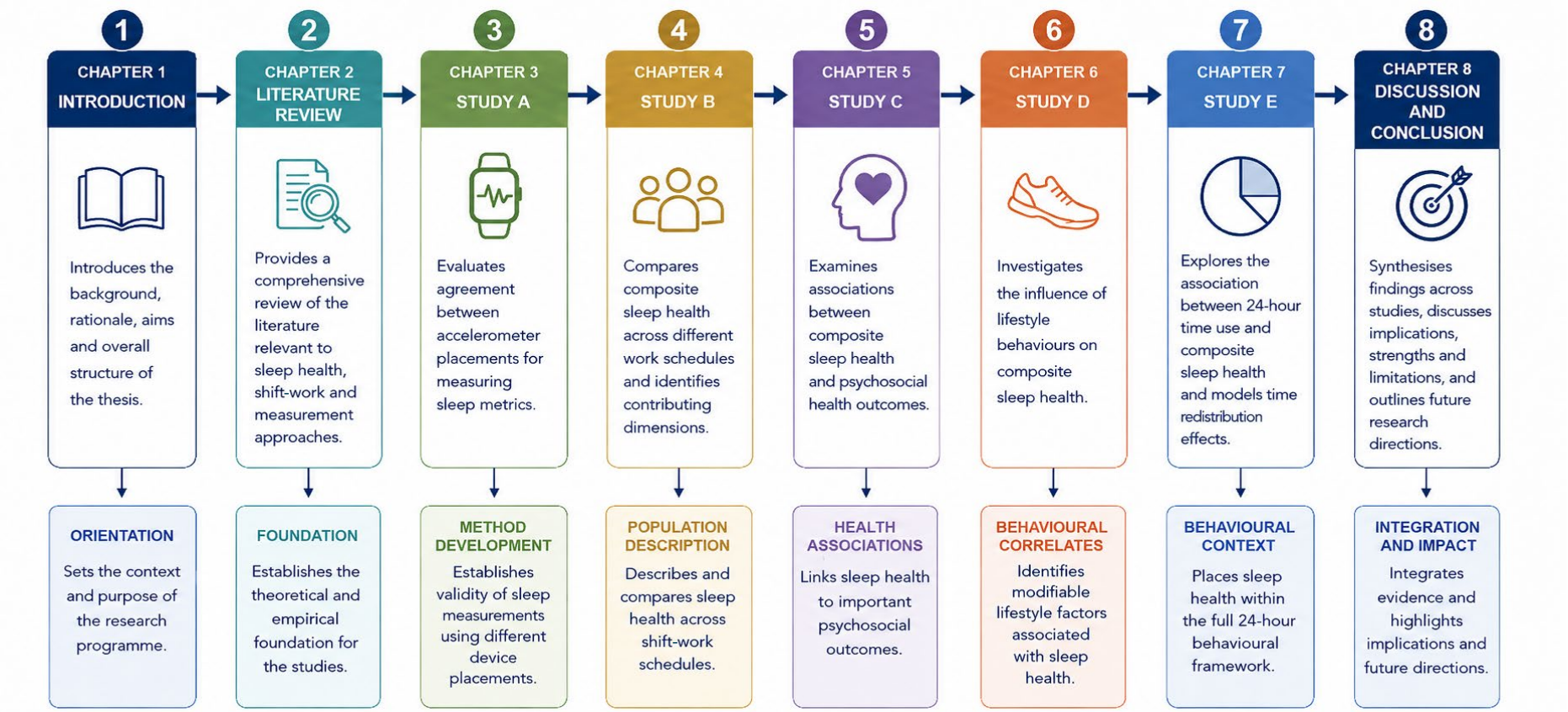



*Figure 1-1. Thesis structure and flow of chapters*

# Chapter 2 – Literature Review

## Introduction

This chapter provides a comprehensive narrative review of the theoretical and empirical literature underpinning the investigation of Composite Sleep Health (CSH) within shift-working populations. The chapter draws on purposive literature searches and citation tracing to synthesise current knowledge relevant to sleep health, shift-work, accelerometery, and 24-hour movement behaviour. In doing so, the chapter establishes the conceptual and methodological foundation necessary to understand how sleep health is measured, experienced, and influenced within occupational settings characterised by irregular work schedules.

The review begins by outlining the biological foundations of sleep, then considers why disrupted sleep is health-relevant and why sleep disruption varies across individuals, populations, and contexts. It then develops sleep health as a multidimensional construct, examines how CSH has been operationalised, and clarifies the role of CSH in this thesis as a pragmatic behavioural-level index rather than a complete representation of sleep health.

Building on this conceptual foundation, the chapter reviews the strengths and limitations of subjective and objective approaches to sleep measurement, with particular emphasis on accelerometery and its application in free-living environments. It then locates sleep within the broader 24-hour behavioural composition, where sleep, sedentary behaviour, and physical activity are interdependent parts of the day.

The chapter then brings these strands together in shift-working populations. Shift-work is examined as a recurrent and occupationally imposed source of sleep disruption, with attention to circadian misalignment, heterogeneous work schedules, health and psychosocial consequences, and behavioural constraints. The chapter concludes by identifying the research gaps that provide the rationale for the studies presented in this thesis.

## Sleep Architecture and Regulation

Sleep is a fundamental biological process regulated by internal mechanisms and external cues that drive its initiation, maintenance, and restorative effects. It contributes to physiological recovery, cognitive functioning, and psychological well-being, and is shaped by both biological timing and behavioural context. These processes are commonly understood through the interaction of sleep-wake homeostasis, circadian regulation, and cognitive-behavioural influences (Carley & Farabi, 2016; Perez-Pozuelo et al., 2020).

Two interdependent processes are central to sleep regulation: Process S and Process C. Process S reflects the homeostatic build-up of sleep pressure during wakefulness, driven partly by the accumulation of adenosine, which inhibits wake-promoting neural activity and increases the propensity for sleep. Process C reflects the circadian regulation of sleep-wake timing through the suprachiasmatic nucleus (SCN) of the hypothalamus, which synchronises internal rhythms with environmental light-dark cues. The SCN coordinates rhythmic physiological processes, including melatonin secretion, which reinforces the timing of sleep but does not directly induce sleep. Sleep therefore emerges from the interaction between accumulated sleep pressure, circadian timing, environmental cues, and learned or behavioural routines (Carley & Farabi, 2016; Perez-Pozuelo et al., 2020).

Sleep is not a uniform state. Rather, it proceeds through cyclical alternation between non-rapid eye movement (NREM) and rapid eye movement (REM) sleep. Across the night, sleep is typically organised into repeated cycles of approximately 90 minutes, although the duration and composition of these cycles vary across the sleep period and between individuals (Au, 2022; Carley & Farabi, 2016). NREM sleep progresses from lighter sleep into slow-wave sleep (SWS), often described as the deepest stage of sleep and characterised by high-amplitude, low-frequency electroencephalographic activity. REM sleep is physiologically distinct, involving rapid eye movements, reduced skeletal muscle tone, and brain activity patterns that differ from NREM sleep (Au, 2022; Carley & Farabi, 2016).

The distribution of sleep stages across the sleep period is not uniform. SWS is more prominent in earlier sleep cycles, reflecting the influence of accumulated homeostatic sleep pressure, whereas REM episodes tend to lengthen across successive cycles and are more prominent later in the sleep period (Au, 2022; Carley & Farabi, 2016). This temporal structure is important because it means that sleep disruption does not necessarily affect all components of sleep equally. Curtailing sleep at the end of the sleep period may disproportionately reduce REM-rich sleep, while fragmentation can interrupt the continuity needed for stable progression through sleep stages. As a result, two individuals may obtain the same total sleep duration but differ in the timing, continuity, and physiological composition of that sleep.

These observations ground the distinction between sleep quantity and sleep quality that recurs throughout this chapter. Quantity refers to the total amount of sleep obtained, whereas quality refers to how effectively the sleep process proceeds, including whether sleep is sufficiently consolidated and continuous to support restorative function, as well as in line with circadian physiology. The two are related but not interchangeable. Insufficient sleep duration limits the opportunity to complete sleep cycles, while fragmented or mistimed sleep can impair sleep quality even when total duration appears adequate. This distinction is supported by evidence that sleep quality may relate more strongly to health, affect, and psychological functioning than sleep duration alone (Pilcher et al., 1997).

This physiological foundation is important for the later development of CSH. Sleep-health metrics such as duration, efficiency, timing, regularity, and variability are behavioural indicators of sleep-wake functioning, but they are grounded in physiological processes that determine when sleep occurs, how consolidated it is, and whether the sleep period provides sufficient opportunity for restorative sleep architecture. The following section therefore considers how disruption to these processes relates to health and population variability.

## Sleep Disruption, Health, and Population Variability

The consequences of insufficient or disrupted sleep justify treating sleep as a health-relevant behaviour rather than simply a matter of comfort or preference. The National Sleep Foundation and the New Zealand Ministry of Health recommend that adults obtain between seven and nine hours of sleep per night (Ministry of Health, 2017; Sleep Foundation, 2021; Watson et al., 2015). Acutely, insufficient sleep impairs cognitive and behavioural functioning, including reaction time, memory retention, decision-making, moral judgement, and vigilance (Lim & Dinges, 2010). It is also associated with increased sympathetic nervous system activation and altered endocrine function (Meerlo et al., 2008). These acute effects have practical consequences, including increased risk of personal injury, traffic accidents, and workplace or industrial accidents (Chattu et al., 2018b). Chronically, insufficient sleep has been associated with metabolic disease, cancers, cardiovascular disease, and total mortality risk (Hillman & Lack, 2013; Li et al., 2022; Yang et al., 2021). These effects extend beyond the individual, because insufficient sleep can contribute to economic costs for workplaces, governments, and healthcare systems (Chattu et al., 2018b). Sleep disruption is therefore a public health concern, not only an individual health behaviour.

However, sleep disruption is not defined by duration alone. The same total sleep duration may not reflect different underlying sleep conditions depending on whether sleep is curtailed, fragmented, mistimed, irregular, or distributed across multiple episodes. This matters because health-relevant sleep impairment may occur through several pathways. A shortened sleep episode limits the opportunity for adequate sleep, a fragmented sleep episode may reduce continuity and consolidation, and a sleep episode occurring at an unfavourable circadian phase may provide less effective recovery even when its duration appears adequate. Sleep timing is therefore not simply a descriptive feature of when sleep occurs, but a potential source of physiological and behavioural disruption.

This is particularly important because sleep timing is shaped not only by biology, but also by social organisation. Human circadian rhythms are aligned with the light-dark cycle, supporting wakefulness during the day and sleep at night. Yet the timing of sleep in

everyday life is also shaped by work schedules, family responsibilities, social expectations, transport demands, and institutional timetables. When externally imposed schedules conflict with biological sleep-wake timing, the resulting mismatch is often described as social jetlag or circadian misalignment (Roenneberg, 2012; Wittmann et al., 2006).

Shift-work represents a particularly clear example of this tension between biological timing and socially organised time. In this context, sleep disruption is not simply a matter of individual choice or poor sleep behaviour. It is partly imposed by employment schedules that require wakefulness during biologically inappropriate periods, sleep during the biological day, exposure to artificial light at night, and recovery within constrained intervals between shifts (Kecklund & Axelsson, 2016; Reutrakul & Knutson, 2015; Vetter, 2020; Wickwire et al., 2017). In this sense, circadian disruption in shift-workers can be understood as a socially and occupationally structured sleep-health burden.

This provides an important bridge to the multidimensional sleep-health framework developed in the next section. If sleep disruption can occur through curtailed duration, reduced continuity, mistimed sleep, irregular sleep patterns, and constrained recovery opportunity, then sleep health is unlikely to be adequately represented by a single sleep metric. A multidimensional approach is therefore useful not because it captures all aspects of sleep, but because it provides a more informative summary of repeated sleep behaviour than duration alone, particularly in shift-workers.

## Sleep Health as a Multidimensional Construct

### Distinguishing sleep, sleep quality, and sleep health

Sleep plays a crucial role in overall health, serving as a foundational pillar in both acute and chronic health maintenance. As understanding of health has evolved, it is increasingly recognised as a dynamic and multidimensional construct influenced by behavioural, biological, and environmental factors. Within this framework, sleep is not simply the absence of wakefulness, but a complex process that contributes to physical restoration, cognitive functioning, and psychological well-being.

Sleep itself is inherently multidimensional and can be conceptualised through the framework of sleep health. Buysse (2014) defined sleep health as a multidimensional pattern of sleep–wakefulness, adapted to individual, social, and environmental demands, that promotes physical and mental well-being. This perspective emphasises that sleep is not a singular outcome, but rather a coordinated system of interrelated dimensions that together determine its effectiveness. The sleep health framework therefore aligns with broader conceptualisations of health, which emphasise optimal functioning and well-being rather than simply the absence of disease (Lee & Lawson, 2021).

By adopting a multidimensional approach, sleep health provides a more comprehensive lens through which to understand how sleep contributes to overall functioning. Disruptions to sleep may occur across multiple dimensions simultaneously, and evaluating these dimensions in isolation may fail to capture the full extent of sleep-related impairment. As such, the conceptualisation of sleep as a multidimensional construct forms the foundation for more comprehensive approaches to sleep measurement and analysis.

## Sleep Health Dimensionality

Building on this conceptual foundation, sleep health can be represented through a composite sleep health (CSH) model, a construct that summarises selected dimensions of sleep within a unified evaluative framework. This approach represents a shift away from traditional sleep research that has often focused on singular outcomes, such as total sleep time or sleep quality, in isolation. While these individual measures provide useful information, they do not fully capture the way different aspects of sleep behaviour combine to shape sleep-wake function and broader health.

One of the most widely recognised approaches to multidimensional sleep health is the SATED framework proposed by Buysse (2014). The original framework included satisfaction, alertness, timing, efficiency, and duration, and was later expanded into Ru-SATED through the addition of regularity (Buysse, 2016). These domains are not simply a list of sleep characteristics. They reflect different ways in which sleep-wake function can

support or disrupt health. Duration represents sleep quantity, efficiency reflects the continuity and consolidation of sleep, timing captures the placement of sleep within the 24-hour day, regularity reflects the consistency of sleep-wake patterns, satisfaction captures the subjective appraisal of sleep, and alertness reflects the functional consequences of sleep during waking times.

The multidimensionality of sleep health is also reflected in the Sleep Health Index (SHI), although its structure differs from the SATED and Ru-SATED frameworks. The SHI was developed as a population-level measure that summarises sleep health across three domains: sleep quality, sleep duration, and disordered sleep (Knutson et al., 2017). This structure is useful because it recognises that sleep health cannot be represented by sleep duration alone. Instead, it combines information about perceived sleep adequacy and continuity, the amount of sleep obtained, and symptoms or indicators of sleep disturbance. The SHI also illustrates that multidimensional sleep health can be operationalised in different ways depending on the purpose of the instrument. Compared with SATED and Ru-SATED, the SHI places greater emphasis on population surveillance and sleep-disorder burden, rather than on representing positive sleep-wake functioning through discrete behavioural dimensions such as timing, efficiency, duration, and regularity. It therefore supports the broader argument that sleep health is multidimensional, while also demonstrating that different CSH approaches may represent different aspects of the sleep-health construct.

The rationale for considering multiple domains together is consistent with Buysse's (2014) broader argument that sleep health operates across multiple levels of analysis. Sleep-wake function is not isolated from health, nor does it operate in only one direction. Sleep affects molecular, cellular, physiological, cognitive, and organism-level function, while health status, behaviour, environment, and waking function also influence subsequent sleep. This reciprocal relationship is central to a sleep-health framework. Poor sleep may contribute to altered endocrine function, immune activity, cardiometabolic regulation, cognitive performance, mood, and behavioural functioning, while illness, stress, pain, environmental disruption, and occupational demands can also degrade sleep duration, continuity, timing, and perceived quality.

Evidence that shows connection to health outcomes can be seen within distinct dimensions of sleep health. Sleep duration has the most established public health recommendations and has been widely linked with cardiometabolic, cognitive, and mortality outcomes (Hillman & Lack, 2013; Li et al., 2022; Lim & Dinges, 2010; Watson et al., 2015; Yang et al., 2021). For example, umbrella-review evidence indicates that, among short sleepers, each one-hour reduction in sleep duration is associated with a 3 to 11% higher risk of outcomes including all-cause mortality, coronary heart disease, stroke, and type 2 diabetes (Li et al., 2022). Sleep continuity and efficiency are also health-relevant because fragmented sleep may reduce the restorative value of the sleep episode, even when total sleep time appears adequate. This is supported by evidence that subjective sleep quality may relate more strongly to health, affect, and psychological functioning than sleep duration alone (Pilcher et al., 1997), and by review-level evidence linking poor sleep quality with increased risk of occupational injuries, coronary heart disease, type 2 diabetes, and depression (Kecklund & Axelsson, 2016). Timing is relevant because sleep occurring at an adverse circadian phase may alter physiological regulation and waking function, particularly where sleep is displaced by work or social schedules. Evidence from shift-work and circadian-misalignment research suggests that sleeping at biologically inappropriate times is associated with impaired alertness, poorer cognitive performance, and adverse physiological outcomes, including altered autonomic function (Grimaldi et al., 2016; Kecklund & Axelsson, 2016; Vanttola et al., 2019; Wickwire et al., 2017). Experimental evidence further suggests that circadian misalignment can impair cardiometabolic regulation, with simulated night-work conditions increasing postprandial glucose by 5.6% in healthy chronic shift-workers (Morris et al., 2016). The cumulative effects of sleep relating to regularity and variability are being increasingly recognised as distinct dimensions because repeated instability may carry health implications beyond average sleep duration (Bei et al., 2016; Sletten et al., 2023; Windred et al., 2024). For example, in a large accelerometery-based cohort, participants in the highest sleep regularity quintile had a 30% lower risk of all-cause mortality than those in the least regular quintile after adjustment for sociodemographic, lifestyle, and health factors (Windred et al., 2024).

Buysse (2014) noted that sleep can be assessed across self-report, behavioural, and physiological levels of analysis, and that most sleep-health domains can be characterised across more than one level . The present thesis focuses on behavioural-level sleep health indicators because it uses repeated, empirical metrics derived from free-living accelerometery to estimate sleep behaviour in shift-workers. This level of analysis is well aligned with the study context because shift-work disrupts sleep through observable behavioural pathways, including curtailed sleep duration, displaced timing, reduced consistency, and night-to-night variability. It also aligns with the later 24-hour movement-behaviour framework, where sleep is examined alongside sedentary behaviour and physical activity. The next section therefore considers how sleep-health dimensions can be represented through measurable behavioural metrics when constructing objective behavioural-level CSH.

## Metric Representation of Sleep Health Dimensions

Once sleep health is understood as multidimensional, constructing a composite model requires each selected dimension to be represented by one or more measurable indicators. These indicators should not be treated as equivalent to the dimensions themselves. Rather, they are empirical approximations of broader sleep-health domains. For example, sleep duration may be represented by total sleep time, sleep continuity may be represented by sleep efficiency or wake after sleep onset, and sleep timing may be represented by sleep onset, offset, or midpoint. Similarly, regularity and variability may be represented through repeated observations of sleep timing or duration across monitoring days. The choice of metric therefore shapes the meaning of the resulting CSH score, because different metrics emphasise different aspects of sleep-wake behaviour.

This distinction is particularly important for objective behavioural-level CSH. Accelerometery can provide repeated estimates of sleep behaviour in free-living conditions, but it does not measure all dimensions of sleep health equally well. Behavioural dimensions such as duration, timing, efficiency, regularity, and variability can be represented through accelerometery-derived indicators. In contrast, satisfaction

requires subjective appraisal of perceived sleep experience, while alertness requires either subjective assessment, objective waking-function testing, or behavioural proxy measures such as napping or rest-activity rhythm indicators. Therefore, the present thesis does not treat accelerometery-derived metrics as complete measures of sleep health. Instead, they are used to represent the behavioural sleep dimensions that can be repeatedly estimated in shift-workers.

The exclusion of satisfaction and alertness from the present CSH model requires explicit clarification. In the SATED and Ru-SATED frameworks, satisfaction captures subjective appraisal of sleep, while alertness reflects waking function (Buysse, 2014; 2016). Satisfaction is not directly amenable to accelerometery because it requires self-report of perceived sleep experience. Alertness is more complex. Actigraphy-derived indicators such as napping and rest-activity rhythm measures may represent an alertness/sleepiness domain in some contexts (Wallace et al., 2021). However, these indicators are not direct measures of perceived alertness, cognitive performance, or waking function, and they were not the focus of the present main sleep-period CSH score. Including alertness would therefore require either subjective assessment, objective waking-function testing, or a separate behavioural proxy such as napping, each of which would shift the construct away from the specific objective behavioural sleep-period CSH used in this thesis. Its exclusion is therefore a methodological boundary, not a rejection of its theoretical importance.

Metric selection also affects comparability across sleep health studies. The same sleep-health dimension may be represented by different indicators, and different indicators within a domain are not necessarily interchangeable. This issue is highlighted by Wallace et al. (2021), who showed that actigraphy-derived sleep measures can be organised into distinct domains of timing, efficiency, duration, alertness/sleepiness, and regularity, but also that specific representative measures are needed to define each domain. For example, sleep efficiency, wake after sleep onset, sleep maintenance, and sleep latency all relate to sleep continuity or efficiency, but they describe different features of the sleep episode. Similarly, sleep midpoint, sleep onset, sleep offset, and wake-up time all relate to sleep timing, but may carry different meanings in populations with irregular or displaced sleep. In shift-workers, these distinctions are especially important because sleep

may occur at atypical times, across split episodes, or with substantial night-to-night variation. As a result, the construction of CSH requires transparent justification not only of the selected dimensions, but also of the metrics chosen to represent them.

The metrics selected for this thesis therefore reflect the behavioural sleep-health dimensions that are conceptually relevant, measurable from the available data, and appropriate for repeated free-living assessment. Duration represents sleep quantity, efficiency represents sleep continuity or consolidation, timing represents the placement of sleep within the 24-hour day, regularity represents consistency of sleep timing, and variability represents instability in sleep duration across repeated observations. These metrics provide a practical way to operationalise objective behavioural-level CSH, while acknowledging that they do not capture subjective satisfaction, perceived sleep quality, direct alertness, waking cognitive performance, or physiological sleep architecture.

## Scoring Approaches in Sleep Health Research

Sleep health scoring has developed primarily from two named approaches to representing multidimensional sleep health: the SATED/Ru-SATED tradition arising from Buysse's sleep-health framework, and the Sleep Health Index (SHI) developed by the National Sleep Foundation (Buysse, 2014; 2016; Knutson et al., 2017). Both approaches have allowed sleep health to be examined as an aggregate construct rather than as a series of isolated sleep variables, but they differ in conceptual emphasis, dimensional structure, and scoring logic. The SATED/Ru-SATED pathway represents sleep health through dimensions of regularity, satisfaction, alertness, timing, efficiency, and duration, whereas the SHI assesses sleep health through sleep quality, sleep duration, and disordered sleep. These differences are important because they show that multidimensional sleep health can be scored in more than one way, depending on whether the emphasis is on positive sleep-wake functioning, population surveillance, sleep disorder burden, or behavioural sleep patterns.

The SATED/Ru-SATED pathway appears to have provided the more flexible basis for subsequent sleep health research. Its dimensional structure allows researchers to adapt

the framework to different data sources, including self-report questionnaires, sleep diaries, actigraphy-derived metrics, mixed subjective and objective indicators, and phenotype-based approaches (Benítez et al., 2020; Brandolim Becker et al., 2018; Meng et al., 2026; Wallace et al., 2021). This adaptability is valuable because it allows CSH to be tailored to different populations and research aims. However, it also creates interpretive challenges, because studies may differ in which domains are included, which metrics represent those domains, what thresholds define healthier or poorer sleep, and how component scores are combined.

By contrast, the SHI provides a more standardised self-report index, with a total score ranging from 0 to 100 (Knutson et al., 2017). This structure is useful for population-level surveillance and comparison, but its domains of sleep quality, sleep duration, and disordered sleep reflect a different measurement emphasis from the objective behavioural-level CSH construct used in this thesis. In particular, the inclusion of disordered sleep gives the SHI a stronger pathology-oriented component, whereas the SATED/Ru-SATED tradition more directly aligns with the positive-health framing of sleep health and the representation of modifiable sleep-wake behaviours.

Across this literature, the key issue is not simply whether sleep health can be scored, but what a given score represents. A composite score requires decisions about the domains included, the metrics used to represent those domains, the thresholds used to classify each metric, and the weighting of each component. Threshold-based scoring can improve interpretability because it allows sleep metrics to be classified in relation to expert recommendations, consensus criteria, or empirical distributions. For example, adult sleep duration recommendations provide a defensible basis for distinguishing insufficient from recommended sleep duration (Watson et al., 2015), and National Sleep Foundation consensus work has used appropriateness categories to classify sleep-quality indicators such as sleep efficiency, wake after sleep onset, sleep latency, and awakenings (Ohayon et al., 2017). However, threshold-based scoring also compresses variation within each domain and may reduce sensitivity to differences that occur within scoring categories.

The use of equal weighting across domains is also common in CSH research but remains a methodological compromise rather than a validated assumption. Equal weighting is

pragmatic because no settled empirical hierarchy establishes that one sleep-health dimension should contribute more strongly than another across all populations and outcomes. However, the relative importance of duration, efficiency, timing, regularity, and variability may differ depending on the population, health outcome, and measurement context. This issue is particularly relevant in shift-workers, where mistimed or irregular sleep may be especially important even when total sleep duration is similar.

The scoring approach used in this thesis aligns most closely with the SATED/Ru-SATED tradition, in which each selected sleep-health dimension contributes to an overall CSH score. The use of a 0, 1, 2 scoring structure allows each dimension to be classified as poorer, intermediate, or healthier sleep health, based on established thresholds where available and empirically derived thresholds where consensus criteria are lacking. This approach preserves the interpretability of a composite score while acknowledging that the score is an operational representation of selected behavioural sleep-health dimensions, not a universal measure of total sleep health.

For these reasons, CSH scores should not be treated as interchangeable across studies without attention to their underlying scoring logic. A total score can summarise an overall sleep-health pattern, but the same total score may arise from different combinations of strengths and deficits across domains. Component dimensions therefore remain important when interpreting CSH. In the present thesis, the total CSH score is used as a pragmatic population-level index of objective behavioural sleep health, while the selected dimensions and scoring thresholds are defined explicitly in the relevant study methods chapters.

## Composite Sleep Health and Health Outcomes

Having established that CSH can be scored in different ways, the next issue is whether aggregate sleep-health scores provide meaningful information about health and functioning. The rationale for CSH depends on more than the idea that sleep is multidimensional. It also depends on evidence that combined sleep-health patterns are associated with health-relevant outcomes. A growing body of research suggests that

better CSH is generally associated with more favourable physical, psychological, and functional outcomes.

Cardiometabolic evidence supports this broader relevance. Multidimensional sleep health has been associated with cardiovascular disease prevalence and cardiometabolic health in US adults (Makarem et al., 2022), while empirically derived sleep-health cut-off scores have been linked with cardiometabolic morbidity in the MIDUS study (Brindle et al., 2019). In clinical populations, multidimensional sleep health has also been associated with glycaemic target achievement in young adults with type 1 diabetes (Griggs et al., 2023). These findings suggest that aggregate sleep-health measures may capture a health-relevant profile of sleep-wake functioning rather than simply reflecting sleep duration alone.

Recent objective evidence strengthens this argument. Using UK Biobank accelerometer data from 85,233 adults, Zhang et al. (2025) developed an Unfavourable Sleep Profile (USP) based on five objectively measured domains: timing, efficiency, duration, rhythmicity, and regularity. The USP classified 18.9% of participants as having an unfavourable multidimensional sleep profile, characterised by later sleep timing, lower sleep efficiency, shorter sleep duration, weaker rhythmicity, and less regular sleep patterns. Over an average follow-up of 7.9 years, USP was associated with 76 of 526 incident disease outcomes, including heart failure (HR 1.35, 95% CI 1.20–1.51), type 2 diabetes (HR 1.31, 95% CI 1.19–1.43), sleep apnoea (HR 1.70, 95% CI 1.45–1.99), all-cause mortality (HR 1.32, 95% CI 1.22–1.42), and cardiovascular disease mortality (HR 1.55, 95% CI 1.32–1.83). Importantly, individual sleep domains produced fewer significant associations than the composite USP, although sleep duration remained strongly associated with many outcomes. These findings provide direct support for the epidemiological value of objective multidimensional sleep-health profiles, while also showing that the particular domains and scoring approach used to define the profile influence the resulting health associations.

CSH has also been examined in relation to mental health and psychosocial outcomes. Aggregate sleep-health scores have been associated with prevalent and incident clinically significant depressive symptoms in older women (Furihata et al., 2017), and with

symptoms of depression among Japanese female hospital nurses (Furihata et al., 2020). Composite sleep-health scores have also been linked with psychological distress, body mass index, and physical functioning in a low-income African American community (DeSantis et al., 2019), and with concurrent mental and physical health outcomes in adolescents prone to eveningness (Dong et al., 2019). Together, these studies indicate that CSH may be relevant across different populations and outcome domains, including mental health, physical functioning, cardiometabolic risk, and disease management.

There is also evidence that multidimensional sleep-health patterns may be relevant to mortality risk. For example, multidimensional sleep characteristics have been examined in relation to mortality in older adults using machine-learning approaches, supporting the idea that sleep-health profiles may provide prognostic information beyond single sleep variables (Wallace et al., 2019). This is important because it strengthens the argument for examining sleep health as a pattern of interacting dimensions, rather than treating each sleep metric as an independent exposure.

Despite this growing evidence base, several limitations remain. First, much of the literature has used self-report or mixed-method CSH scores, meaning that associations with health outcomes may partly reflect subjective sleep experience, perceived alertness, or symptoms of sleep disturbance. These are important aspects of sleep health, but they are not equivalent to objective behavioural-level CSH. Second, scoring approaches vary across studies, including the domains selected, metrics used, thresholds applied, and weighting of individual components. This makes it difficult to determine whether observed associations reflect multidimensional sleep health as a broad construct, or the particular combination of indicators used in each study.

A further limitation is that most evidence has been developed in general population, older adult, adolescent, or clinical samples. Less is known about whether similar associations are observed in shift-workers, whose sleep is often shaped by externally imposed schedules, circadian misalignment, and restricted recovery opportunity. This distinction matters because a low CSH score may reflect different underlying mechanisms in shift-workers than in non-shift-working populations. For example, short sleep, irregular timing,

and poor efficiency may arise from occupational constraints rather than only from individual sleep behaviour.

Taken together, existing evidence supports the use of CSH as a population-level indicator of sleep-health patterns associated with physical, mental, and psychosocial outcomes. However, this evidence does not establish CSH as a universal or causal measure of health risk. Rather, it shows that multidimensional sleep-health scores can provide useful epidemiological information when their construction and interpretation are clearly specified. For the present thesis, this supports examining whether objective behavioural-level CSH differs across work-pattern groups and whether it is associated with health-relevant outcomes in shift-workers.

## Sleep Health Data Collection

The preceding section established that CSH is an operational representation of selected sleep-health dimensions. However, the meaning of any CSH score also depends on the method used to measure sleep. Different measurement approaches capture different levels of sleep information, including self-reported sleep experience, behavioural sleep-wake patterns, and physiological sleep architecture. This distinction is central to the present thesis, which examines objective behavioural-level CSH derived from free-living accelerometery rather than questionnaire-based sleep health or laboratory-based physiological sleep.

Measurement choice is especially important in multidimensional sleep-health research because no single method captures all aspects of sleep equally well. Self-report and diary-based approaches provide information about perceived and reported sleep, but are influenced by recall, interpretation, and reporting accuracy (Buysse et al., 1989; Cespedes et al., 2016; Krystal & Edinger, 2008). Polysomnography provides detailed physiological information about sleep staging and architecture, but is less suited to repeated, free-living measurement across multiple days. Accelerometery provides a practical method for estimating repeated sleep-wake behaviour in naturalistic settings, but sleep is inferred

from movement or inactivity rather than measured directly (Ancoli-Israel et al., 2015; Smith et al., 2018). These differences do not make one method universally superior. Rather, they determine what level of sleep health can be validly represented.

## Subjective and Objective Approaches to Sleep Measurement

Sleep has commonly been assessed through subjective methods, objective physiological methods, and objective behavioural methods. Subjective approaches include questionnaires and sleep diaries. These are widely used because they are low cost, scalable, and able to capture sleep over extended timeframes. Questionnaires are particularly useful for large epidemiological studies because they can assess habitual sleep patterns across large samples. Sleep diaries provide more temporally specific information and can help identify intended sleep periods, bedtimes, wake times, naps, and irregular sleep schedules. However, subjective approaches depend on participant interpretation and reporting, and retrospective questionnaires may be affected by recall bias. Comparisons between self-reported and actigraphy-derived sleep duration also show that these methods do not necessarily produce equivalent estimates, reinforcing the importance of distinguishing reported sleep from objectively estimated sleep behaviour (Cespedes et al., 2016; Faerman et al., 2020).

Polysomnography (PSG) is widely regarded as the reference standard for physiological sleep measurement because it records neurophysiological signals that allow sleep and wake to be classified directly and sleep architecture to be examined. PSG is therefore essential for clinical diagnosis and for research questions requiring information about sleep stages, respiratory events, arousals, and other physiological features of sleep. However, PSG is resource-intensive, may alter usual sleep because of the monitoring context, and is often limited to one or a small number of nights. These characteristics make it less practical for large-scale, repeated, free-living assessment of habitual sleep behaviour (Ancoli-Israel et al., 2015; Smith et al., 2018).

Objective behavioural methods, including actigraphy and accelerometery, occupy a different measurement position. These methods do not measure physiological sleep

directly but provide repeated measurement of movement and rest patterns from which sleep-wake behaviour can be estimated. Actigraphy has demonstrated high sensitivity for detecting sleep relative to PSG, although specificity for detecting wake is generally lower, meaning that quiet wakefulness may be misclassified as sleep (Ancoli-Israel et al., 2015; Marino et al., 2013). Clinical guidance supports actigraphy as a useful method for evaluating sleep-wake patterns and circadian rhythm sleep-wake disorders, while recognising that it is not equivalent to PSG for measuring sleep physiology (Smith et al., 2018). For the present thesis, this distinction supports the use of accelerometery to estimate behavioural sleep patterns across repeated free-living observations.

## Accelerometery and Free-Living Sleep Assessment

Accelerometery has become an important method for sleep research because it can capture repeated sleep-wake estimates across multiple days in naturalistic conditions. This is particularly useful for population, occupational, and 24-hour movement-behaviour studies, where the aim is often to examine how sleep occurs within everyday routines rather than under laboratory conditions (Ancoli-Israel et al., 2015; Smith et al., 2018). In this context, accelerometery provides a practical basis for deriving sleep metrics that can be examined alongside sedentary behaviour and physical activity across the 24-hour day.

Open-source processing tools have improved the transparency and reproducibility of accelerometer-based sleep and movement-behaviour research. GGIR, for example, provides a standardised approach for processing raw accelerometer data and deriving sleep and physical activity metrics across multi-day monitoring periods (Migueles et al., 2019b). Within GGIR, sleep analysis involves two related but distinct tasks: identifying sustained inactivity and defining the sleep-period window within which that inactivity is interpreted as sleep (van Hees & Migueles, n.d.). This distinction is important because different sleep algorithms address these tasks in different ways.

Traditional actigraphy algorithms, including Cole-Kripke and Sadeh, commonly classify sleep and wake from epoch-level activity counts, with movement across short time intervals compared against threshold-based rules (Cole et al., 1992; Fekedulegn et al.,

2020; Sadeh et al., 1994). These approaches have an established evidence base, particularly for wrist actigraphy. However, they are also tied to count-based processing, device-specific assumptions, epoch length, and, in some cases, diary-, event-marker-, or manually reviewed sleep windows. This can create challenges for large free-living studies because sleep-period definition may require participant logs, manual checking, or assumptions about when sleep is expected to occur. It can also limit transferability when data are collected using raw accelerometery or from body locations other than the wrist.

The sustained inactivity bout approach developed by van Hees et al. (2015) takes a different approach by using changes in accelerometer angle rather than activity counts. Instead of relying on epoch-level count thresholds alone, it identifies sustained periods in which device orientation changes very little over time. This makes the approach well suited to raw accelerometer processing because it provides a transparent and reproducible method for identifying sleep-relevant inactivity. Importantly, this does not mean that the van Hees approach is universally superior to count-based algorithms. Rather, its strength for the present thesis is that it is interpretable, implemented in an open-source pipeline, compatible with raw accelerometery, and able to be applied consistently across the monitoring locations used in the agreement study in the next chapter.

Recent validation work reinforces the importance of algorithm and placement decisions. In a PSG validation study of children and adolescents, Meredith-Jones et al. (2024) compared 11 sleep algorithms across Actigraph and Axivity devices worn at the wrist, waist, lower back, and thigh. The study found that count-based sleep algorithms varied markedly in performance, that wrist-worn devices generally provided more accurate estimates of most sleep outcomes than hip, thigh, or lower-back placement, and that the most appropriate algorithm depended on the sleep measure of interest. Although this evidence was generated in an adolescent sample and should not be generalised directly to adult shift-workers, it demonstrates that sleep estimates are shaped by the interaction between algorithm, device placement, and outcome metric.

Diary-free approaches have also been developed for large-scale studies where sleep diaries are unavailable. For example, van Hees et al. (2018) proposed a heuristic for

estimating sleep parameters from accelerometer data without diary information. Machine-learning approaches have also been developed to improve automated sleep-wake classification using accelerometer data (Sundararajan et al., 2021). These methods are valuable for large epidemiological datasets, but they depend on assumptions built into the algorithm, training data, and population context. Their performance may therefore vary when applied to populations with irregular sleep-wake schedules, such as shift-workers.

In the present thesis, the availability of sleep diary information further supported the use of a diary-guided sustained inactivity bout approach. This is particularly relevant because sleep timing may be irregular in shift-workers, and because the main sleep episode may occur outside conventional nocturnal windows (Kecklund & Axelsson, 2016; Vanttola et al., 2019; Wickwire et al., 2017). The selected approach therefore aligns with the available data, the need for reproducible processing, the use of raw accelerometery, and the aim of deriving repeated behavioural sleep metrics for CSH.

## Methodological Challenges in Accelerometer-Based Sleep Measurement

Although accelerometery is useful for repeated free-living sleep assessment, several methodological challenges affect how accelerometery-derived sleep metrics should be interpreted. The first challenge is classification accuracy. Validation studies show that actigraphy generally performs better for identifying sleep than wake, with lower specificity for wake detection relative to PSG (Ancoli-Israel et al., 2015; Marino et al., 2013). This can affect estimates of sleep duration, wake after sleep onset, and sleep efficiency, particularly in contexts where quiet wakefulness is likely.

A second challenge concerns sleep-period identification. Accelerometer algorithms must distinguish the intended sleep episode from other periods of rest or low activity. This decision may be more difficult in populations whose sleep occurs outside conventional nocturnal periods or varies substantially across days. In shift-workers, sleep timing may be shaped by early starts, late finishes, night shifts, recovery days, and quick returns, all of which can complicate assumptions about when sleep is expected to occur (Kecklund &

Axelsson, 2016; Vanttola et al., 2019; Wickwire et al., 2017). The methodological issue is therefore not only whether sleep-like rest can be detected, but whether the detected rest corresponds to the relevant sleep episode.

Wear location is another important consideration. Much of the evidence base for actigraphy-derived sleep estimation has been developed using wrist-worn devices, where movement patterns are strongly related to sleep-wake behaviour (Ancoli-Israel et al., 2015; Smith et al., 2018). However, accelerometers are also used at other body locations in 24-hour movement-behaviour research, including the thigh and lower back, because these placements can support the estimation of waking behaviours such as posture, sedentary time, and physical activity (Chastin et al., 2015; Dumuid et al., 2018). These placements may therefore be advantageous for broader time-use research, but their validity for estimating sleep is less established than wrist-worn actigraphy. This concern is supported by validation evidence showing that sleep estimates differ by device placement and algorithm, with wrist placement generally performing better than thigh, lower-back, or hip placement for several sleep outcomes (Meredith-Jones et al., 2024). Applying sleep algorithms across body locations therefore requires caution, because differences in movement signal, posture, and device orientation may influence sleep-wake classification.

A further challenge is that some sleep-health dimensions require repeated observation across several days. Metrics such as mean sleep duration or average sleep efficiency may be estimated from a smaller number of nights, but regularity and variability require repeated observations of timing and duration. Short monitoring periods may therefore be less reliable for estimating the stability of sleep-wake patterns. This is important for CSH because a multidimensional score may include both average sleep characteristics and measures of night-to-night consistency. The accuracy of the composite score therefore depends partly on whether the monitoring period is sufficient to characterise the selected dimensions (Bei et al., 2016; Sletten et al., 2023; Windred et al., 2024).

Thus, sleep-period identification, wear location, monitoring duration, and population context all influence the sleep estimates used to construct CSH. The following section

therefore considers the implications of these measurement issues for objective behavioural-level CSH in the present thesis.

## Implications for Objective Measurement of Behavioural-Level CSH

The measurement issues described above have direct implications for the construction and interpretation of an objective behavioural-level CSH. A composite score depends on the selected sleep metrics being estimated consistently enough to provide a meaningful summary of sleep behaviour. When those metrics are derived from accelerometery, the resulting score is shaped by the algorithm used, the monitoring location, the number of valid days, and the population context. These considerations are particularly important for dimensions such as timing, regularity, and variability, where repeated observations are required and where irregular sleep schedules may affect both estimation and interpretation.

This does not undermine the use of accelerometery-derived CSH, but it clarifies what the construct represents. In the present thesis, CSH is used as a population-level index of objective behavioural sleep patterns, rather than as a measure of physiological sleep architecture or total sleep health. This framing is consistent with the broader sleep-health framework, which recognises that sleep can be examined across self-report, behavioural, and physiological levels of analysis (Buysse, 2014). It is also consistent with actigraphy-based sleep-health research showing that objective sleep metrics can be organised into multidimensional domains relevant to sleep health (Wallace et al., 2021).

For the present thesis, the key measurement question is whether the accelerometery-derived sleep metrics required for CSH can be estimated sufficiently from the available wear locations. This is important because wrist-worn actigraphy has the strongest sleep-measurement evidence base, whereas thigh and low-back accelerometery are more commonly used in 24-hour movement-behaviour research for estimating waking behaviours. The empirical studies that follow therefore begin by examining agreement between sleep metrics derived from wrist, thigh, and low-back accelerometery, before applying objective behavioural-level CSH in shift-workers.

## Sleep, Time-use, and Health Behaviours

The preceding sections established CSH as a multidimensional representation of sleep health and outlined the measurement considerations involved in deriving objective behavioural sleep metrics. However, the relevance of CSH also depends on whether these sleep-health profiles are meaningfully related to health-relevant outcomes and behaviours. These relationships can be considered across different levels of daily life, including psychosocial and wellness outcomes, self-reported health behaviours, and objectively measured waking behaviours. This distinction is central to the present thesis, because objective behavioural-level CSH is examined not only as a measurement construct, but as a potential indicator of health-relevant variation in shift-workers.

The type of outcome or behaviour being examined is important because each provides different information about the role of sleep health. Psychosocial and wellness indicators provide insight into whether CSH is associated with perceived functioning, stress, resilience, and symptoms of strain. Self-reported behaviours, such as physical activity, caffeine intake, alcohol use, smoking, diet, and sleep-aid use, provide information about lifestyle factors that may relate to sleep health (Alnawwar et al., 2023; Irish et al., 2015). Objectively measured movement behaviours provide a further perspective by situating sleep within the broader distribution of sedentary behaviour, light physical activity, and moderate-to-vigorous physical activity across the 24-hour day (Chastin et al., 2015; Dumuid et al., 2018; Rosenberger et al., 2019). These differences do not make one form of evidence more important than another. Rather, they define the level at which CSH is being evaluated, beginning with its relationship to psychosocial functioning and well-being.

### Psychosocial and Wellness Correlates of Composite Sleep Health

Sleep function is closely connected with psychosocial functioning and well-being. Poor sleep may contribute to psychological strain, fatigue, reduced recovery capacity, and reduced perceived ability to manage daily demands, while stress and poorer psychological

well-being may also contribute to poorer sleep (Allen et al., 2019; Lee & Lawson, 2021). This reciprocal relationship means that sleep health is relevant not only to physical health outcomes, but also to everyday functioning, resilience, and symptoms of strain. These outcomes are particularly relevant when sleep is examined in working populations, where sleep may be shaped by occupational schedules, workload, and recovery opportunity.

Multidimensional sleep-health research has begun to examine these relationships using aggregate sleep-health scores. Higher sleep health has been associated with more favourable psychological and physical well-being (Lee & Lawson, 2021), while poorer multidimensional sleep health has been associated with depressive symptoms in population and occupational samples (Furihata et al., 2017; 2020). These findings support the value of examining sleep health as a multidimensional construct, because psychosocial functioning may be shaped by more than sleep duration alone.

However, the existing evidence also has limitations from the perspective of objective behavioural-level CSH. Several multidimensional sleep-health studies have used self-reported or mixed-method sleep-health measures, which may partly overlap with subjective well-being, perceived sleep disturbance, or daytime functioning. This issue is not entirely unrecognised in the literature. For example, Lee and Lawson (2021) found that sleep satisfaction was one of the strongest contributors to associations with perceived stress and physical health, while Furihata et al. (2017) acknowledged limitations related to retrospective self-reported sleep and the direction of cross-sectional associations. Nevertheless, these studies do not fully resolve whether objectively measured behavioural sleep-health profiles show similar relationships with psychosocial outcomes when subjective satisfaction and alertness are excluded from the CSH score.

Directionality is another important limitation. Poor sleep health may contribute to perceived stress, burnout, depressive symptoms, somatic or cognitive strain, and self-reported sleeping troubles, but these outcomes may also impair sleep continuity, timing, and recovery. These outcomes are also unlikely to be entirely independent of one another, because perceived stress, burnout, depressive symptoms, cognitive stress, somatic stress, resilience, and sleeping troubles may reflect related aspects of strain and recovery. Cross-sectional associations between multidimensional sleep health and these outcomes

therefore need to be interpreted as evidence of relationship rather than evidence of causal direction.

These issues are particularly relevant in shift-workers. Shift-work is consistently associated with sleep disturbance, fatigue, and impaired well-being (Kecklund & Axelsson, 2016; Wickwire et al., 2017). However, low sleep health in shift-workers may reflect externally imposed work schedules, circadian misalignment, and restricted recovery opportunity, rather than individual sleep behaviour alone. This does not mean that sleep health should be interpreted only at the population level, but it does mean that behavioural sleep-health profiles in shift-workers need to be understood within an occupational context. The present thesis addresses this gap by examining whether objective CSH is associated with resilience, perceived stress, burnout, depressive symptoms, somatic and cognitive stress, general health, and self-reported sleeping troubles in shift-workers. This extends the literature by testing whether an accelerometery-derived CSH score, excluding subjective satisfaction and alertness, has relevance beyond measurement and group comparison.

## Self-Reported Health Behaviours and Sleep Health

Lifestyle and health-related behaviours are frequently discussed in relation to sleep because many are potentially modifiable and are commonly included in sleep-hygiene guidance. These behaviours include physical activity, dietary patterns, caffeine and alcohol consumption, smoking, daytime napping, and the use of sleep aids (Irish et al., 2015). They are relevant because they may be associated with sleep timing, sleep continuity, sleep duration, physiological arousal, or perceived sleep quality. However, much of this evidence has been developed in relation to individual sleep outcomes, sleep-hygiene components, or sleep problems, rather than multidimensional sleep health (Alnawwar et al., 2023; Irish et al., 2015; Skarpsno et al., 2018). This limits understanding of whether these behaviours correspond to an overall pattern of better or poorer CSH.

The relationship between self-reported health behaviours and sleep is also unlikely to operate in only one direction. Irish and colleagues (2014) noted that sleep is associated

with waking health behaviours, including alcohol use, caffeine use, smoking, and exercise, but that the causal direction of these relationships is not always clear. This is important because some behaviours may influence sleep through physiological or behavioural pathways, while others may also reflect responses to tiredness, stress, or existing sleep difficulty. For example, caffeine may disrupt sleep when consumed close to bedtime, but caffeine use may also reflect attempts to manage fatigue (Drake et al., 2013). Alcohol may be used to facilitate sleep onset, despite evidence that it can disrupt later sleep continuity and sleep architecture (Gardiner et al., 2024). Sleep-aid use may indicate existing sleep difficulty, while smoking has been associated with sleep disturbance, shorter sleep duration, longer sleep latency, and altered sleep architecture (Costa & Esteves, 2018). These examples support treating self-reported health behaviours as correlates of CSH, rather than as behavioural determinants of sleep health.

Physical activity is one of the most consistently examined behavioural correlates of sleep. Evidence suggests that physical activity is associated with more favourable sleep outcomes, including sleep duration, sleep efficiency, and subjective sleep quality, although findings vary by activity intensity, timing, and domain (Alnawwar et al., 2023; Kubala et al., 2020; Skarpsno et al., 2018). This variability is important because leisure-time physical activity may have different associations with sleep than occupational physical activity, and light, moderate, and vigorous activity may not relate to sleep in the same way (Kubala et al., 2020; Skarpsno et al., 2018). Kubala et al. (2020) is particularly relevant because physical activity was examined in relation to a composite measure of sleep health, rather than only a single sleep metric. However, that measure included self-reported sleep-health dimensions, meaning that further work is still needed to examine whether health behaviours relate to objective behavioural-level CSH.

Dietary patterns may also be relevant to sleep, although the strength and direction of associations vary depending on the dietary exposure and sleep outcome examined (Alnawwar et al., 2023). This illustrates a broader issue in the behavioural sleep literature. Health-related behaviours may be associated with sleep through different pathways, including physiological arousal, energy balance, mood regulation, substance effects,

routines, or underlying health and stress. As a result, a behaviour may relate to one aspect of sleep without corresponding to better or poorer sleep health overall.

Collectively, this literature indicates that self-reported health behaviours are relevant to sleep, but two limitations remain from a CSH perspective. First, much of the evidence focuses on individual sleep dimensions or subjective sleep outcomes, meaning that associations with objective multidimensional sleep health remain less clear. Second, when both behaviours and sleep are measured by self-report, associations may be influenced by recall, perception, or shared reporting method. The present thesis partly addresses this limitation by examining whether self-reported health-related behaviours are associated with objectively measured CSH in shift-workers. This provides a behavioural context for CSH before moving to the more specific question of objectively measured movement behaviours and the distribution of time across the 24-hour day.

## Objectively Measured Physical Activity, Sedentary Behaviour, and 24-hour Time Use

Self-reported health behaviours provide useful information about lifestyle factors that may relate to sleep, but they do not fully capture how sleep and waking behaviours are distributed across the day. Caffeine intake, alcohol use, smoking, diet, and sleep-aid use occur within the 24-hour day; however, these behaviours are not mutually exclusive categories of time use, nor do they collectively account for how the full day is allocated. In contrast, sleep, sedentary behaviour, light physical activity, and moderate-to-vigorous physical activity can be understood as time-use behaviours because, together, they occupy the finite 24-hour period. Time spent in one of these behaviours necessarily reduces the time available for the others.

This recognition has led to increasing interest in the 24-hour activity cycle. Sleep does not occur in isolation, but sits alongside sedentary behaviour, light physical activity, and moderate-to-vigorous physical activity as mutually exclusive and exhaustive parts of the day (Rosenberger et al., 2019). The interdependence of sleep and waking behaviours is

reflected in bidirectional relationships, where sleep may influence daytime functioning, energy levels, and motivation for activity, while physical activity and sedentary behaviour may influence sleep duration, quality, and timing (Johansson et al., 2023; Perez-Pozuelo et al., 2020). From this perspective, sleep is not simply an isolated outcome, but part of a broader behavioural system.

Traditional analyses of physical activity and sedentary behaviour have often treated waking behaviours as independent exposures. However, this is problematic for time-use data because daily behaviours are co-dependent. Increasing time in one behaviour necessarily requires decreasing time in one or more other behaviours. Compositional Data Analysis (CoDA) has therefore emerged as a key methodological approach for analysing time-use data. CoDA treats time spent in different behaviours as parts of a whole, allowing the relative distribution of behaviours to be examined in relation to health outcomes. Chastin and colleagues (2015) provided an early application of CoDA to movement behaviours by examining the combined effects of time spent in sleep, sedentary behaviour, and physical activity on obesity and cardiometabolic markers. Dumuid et al. (2018) subsequently formalised the use of CoDA for physical activity, sedentary time, and sleep research, outlining how daily behaviours can be analysed as parts of a whole rather than as independent exposures. Later methodological work has further reinforced the value of CoDA for time-use epidemiology while also noting challenges in interpretation and communication (Dumuid et al., 2020).

Building on this, isotemporal substitution models provide a way to estimate the potential association of reallocating time between behaviours. For example, replacing sedentary time with light physical activity or moderate-to-vigorous physical activity has been associated with more favourable cardiometabolic and mental health outcomes (Curtis et al., 2023; Dumuid et al., 2022b). These approaches provide practical insight into how changes in the distribution of daily behaviours may relate to health. However, reallocation estimates should not be interpreted as direct evidence of intervention effects. They describe statistical associations between alternative time-use distributions and outcomes, not whether a specific behavioural change is feasible or causal for a given population. This distinction is particularly important in shift-workers, where sleep opportunity, fatigue,

recovery time, and work schedules may constrain how time can realistically be redistributed.

Despite this methodological development, the integration of multidimensional sleep health within time-use epidemiology remains limited. Time-use approaches provide a useful framework for examining how sleep and waking movement behaviours are distributed across the 24-hour day. However, within this literature, sleep is commonly represented as time allocated to one part of the daily composition, rather than as a multidimensional sleep-health construct. This approach is useful for studying sleep duration as part of the 24-hour day, but it does not capture other dimensions of sleep health such as efficiency, timing, regularity, and variability.

Recent work has begun to address this limitation. Matricciani et al. (2024) examined associations between 24-hour activity composition and dimensions of healthy sleep in Australian children and adults. In that study, the daily composition was represented by actigraphy-derived sleep duration, sedentary time, light physical activity, and moderate-to-vigorous physical activity, while healthy sleep was examined across continuity/efficiency, timing, alertness/sleepiness, satisfaction/quality, and regularity. The findings showed that the 24-hour activity composition was associated with both objectively measured and self-reported dimensions of healthy sleep. This provides important evidence that sleep can be examined not only as a duration-based component of the 24-hour day, but also in relation to broader sleep-health dimensions.

This work is particularly relevant to the present thesis as it brings together two areas that have developed separately: time-use epidemiology and multidimensional sleep health. It also aligns with earlier multidimensional sleep research showing that objective and self-report sleep dimensions may provide distinct information. For example, Matricciani et al. (2022) found that both actigraphy-derived sleep characteristics and self-reported troubled sleep associated with poorer cardiometabolic health independent of objective sleep parameters. Together, these studies support the value of examining sleep as a multidimensional construct, while also showing that subjective, objective, and mixed-method sleep health indicators should not be treated as equivalent.

This emerging literature, however, does not fully fulfil the ambition of the present thesis. Matricciani et al. (2024) examined individual dimensions of healthy sleep rather than a single objective CSH score and included both objective and self-reported sleep health dimensions. The sample was also drawn from Australian children and adults, rather than from shift-workers whose sleep timing, recovery opportunity, and daily behaviour may be shaped by occupational schedules. As a result, it remains unclear whether objectively measured CSH is associated with 24-hour time use in shift-working populations.

This creates both an opportunity and an interpretive challenge for CSH research. The opportunity is that CSH allows time-use research to move beyond sleep duration and examine whether the distribution of time across sleep and waking movement behaviours is associated with a multidimensional sleep-health profile. The challenge is that sleep duration may be included both as part of the 24-hour time-use composition and as one component of the CSH outcome. As a result, any observed association between time use and CSH may be partly driven by the sleep-duration component of the outcome itself, making it difficult to determine whether relationships reflect sleep duration specifically or broader aspects of sleep health.

This issue does not preclude examining CSH within a time-use framework, but it does require clear interpretation of the total CSH score alongside the componentry of 24-hour time use. In doing so, CSH research can extend time-use epidemiology by treating sleep not only as time allocated within the 24-hour day, but also as a multidimensional health-related outcome. These issues become particularly important when CSH is examined in occupational populations where sleep timing, recovery opportunity, and daily behaviour are shaped by work schedules. The following section therefore turns to shift-work as the occupational context for applying objective behavioural-level CSH.

# Composite Sleep Health in Shift-Working Populations

Shift-work is the occupational context in which the preceding conceptual and methodological issues come together. The earlier sections established that sleep is biologically regulated, health-relevant, multidimensional, measurable at a behavioural level, and embedded within the 24-hour distribution of daily behaviour. The preceding section also showed that the integration of multidimensional sleep health into 24-hour time-use research has begun but remains limited in relation to objective CSH and shift-working populations. Shift-work therefore provides a critical context for applying this framework because sleep disruption is often recurrent, externally imposed, and expressed across multiple sleep-health dimensions. Rather than affecting sleep duration alone, non-standard work schedules may influence when sleep occurs, how consolidated it is, how regular it remains across days, and how much opportunity is available for recovery.

Shift-work itself is not a uniform exposure. Shift-workers may differ in night-work exposure, rotation pattern, shift timing, quick returns, recovery opportunity, and the balance between workdays and non-workdays. These differences mean that the sleep-health burden of shift-work may not be distributed evenly across all forms of non-standard work. At the same time, field-based occupational studies often require pragmatic classification decisions, particularly when sample size, roster detail, or study aims limit the extent to which shift-work subgroups can be analysed separately. In this thesis, work-pattern heterogeneity is therefore treated as both a substantive issue and an interpretive consideration: it is examined directly where group comparison is central to the research question, and it informs the interpretation of studies where shift-workers are analysed as a consolidated occupational group.

## Shift-Work as an Occupational Sleep-Health Context

Shift-work is commonly used to describe employment schedules that occur outside conventional daytime hours and may require work during periods typically allocated to

sleep (Silva et al., 2020). In New Zealand, non-standard working hours are common. Stats NZ's 2018 Survey of Working Life reported that 67% of workers at least occasionally worked outside standard hours of 7 a.m. to 7 p.m. Monday to Friday, while 23.3% reported working night shifts between 11 p.m. and 5 a.m. (Statistics New Zealand, 2018). This places shift-work within a broader social and occupational context, where 24-hour services, transport, health, security, aviation, and other industries depend on labour outside conventional daytime schedules.

The term shift-work, however, covers a wide range of working patterns rather than a single exposure. These may include permanent night work, rotating shifts, early starts, late finishes, irregular shifts, split shifts, or schedules that differ in the speed, direction, and predictability of rotation (Wickwire et al., 2017). This variation is one reason why findings across shift-work studies can be difficult to compare. Workers classified under the same broad category may experience different levels of circadian misalignment, sleep restriction, recovery opportunity, and social disruption.

This limitation is visible in field-based work that has examined sleep in relation to specific shift contexts. Vanttola et al. (2019), for example, studied sleep and alertness across morning shifts, evening shifts, night shifts, and days off in shift-workers with and without shift-work disorder symptoms. Their findings showed that sleep and alertness varied by shift context and symptom status, supporting the view that the sleep burden of shift-work is not evenly distributed across all working patterns. At the same time, this type of detailed shift-specific assessment is not always feasible in larger occupational studies, where sample size, roster data, and monitoring duration may limit the number of meaningful work-pattern categories that can be compared.

For CSH research, this creates a methodological tension. Treating all shift-workers as one group may obscure meaningful differences in sleep metrics. Yet highly detailed work-pattern classifications may produce small subgroups, reducing precision and limiting the interpretability of associations. A useful approach is therefore to recognise shift-work heterogeneity without assuming that every study must disaggregate it in the same way. Work-pattern distinctions are most informative when the research question is specifically

concerned with group differences, while consolidated shift-worker samples may be appropriate when the aim is to examine associations within a shift-working population.

## Circadian Disruption, Sleep Opportunity, and Recovery

The sleep-related burden of shift-work is grounded in the mismatch between work/wake schedules and the biological regulation of sleep and wakefulness. As outlined earlier, sleep is shaped by the interaction between homeostatic sleep pressure and circadian timing. Shift-work disrupts this interaction by requiring wakefulness, alertness, eating, commuting, and social functioning at times when the body may be biologically prepared for sleep, and by requiring sleep at times when circadian alerting signals and environmental conditions may oppose it (Kecklund & Axelsson, 2016; Wickwire et al., 2017).

This disruption is not limited to night shifts. Night work is a clear source of circadian misalignment, but early morning shifts, quick returns, extended shifts, and rapidly rotating schedules can also restrict sleep opportunity and reduce recovery time (Kecklund & Axelsson, 2016; Vanttola et al., 2019). Sleep after night work is often shortened by circadian wake-promoting signals and by daytime environmental and social conditions, while sleep before early starts may be curtailed by the need to wake during the biological night or early morning (Kecklund & Axelsson, 2016; Wickwire et al., 2017). These schedule-related constraints may affect several sleep-health dimensions, including duration, timing, efficiency, regularity, and night-to-night variability.

The strength of this literature is that it clearly establishes shift-work as a context in which sleep opportunity and sleep timing are repeatedly challenged. Its limitation is that sleep is still often represented through single outcomes, such as total sleep time, insomnia symptoms, sleepiness, or sleep quality, rather than through a multidimensional sleep-health profile (Kecklund & Axelsson, 2016; Vanttola et al., 2019). This matters because the same broad category of shift-work may include different patterns of sleep disruption. Early starts may primarily curtail sleep and shift wake timing earlier, while night shifts may displace sleep into the day and increase irregularity across workdays and non-workdays.

These distinctions are difficult to capture when sleep is assessed through duration or sleep complaints alone.

Recovery opportunity is also central to interpreting sleep health in shift-workers. Sleep lost across work periods may be partially compensated for on days off, but recovery itself may vary according to roster structure, consecutive shifts, quick returns, family responsibilities, and individual differences in adaptation (Kecklund & Axelsson, 2016; Vanttola et al., 2019; Wickwire et al., 2017). This is relevant to CSH because repeated free-living measurement can capture not only average sleep duration, but also whether sleep timing and duration remain stable across the monitoring period. In this way, objective behavioural-level CSH can describe the accumulated sleep-health pattern associated with shift-work, rather than relying only on isolated sleep episodes or subjective sleep complaints.

## Health and Functional Consequences of Shift-Work Sleep Disruption

The disruption of sleep associated with shift-work has important implications for physical health, psychological functioning, and occupational safety. The strongest indication of broader health relevance is the IARC Monographs classification of night shift-work involving circadian disruption as probably carcinogenic to humans, Group 2A (International Agency for Research on Cancer, 2019). This classification identifies night shift-work as a potential carcinogenic hazard, rather than a direct estimate of individual cancer risk, but it demonstrates the level of concern attached to long-term circadian disruption in occupational health.

Cardiometabolic evidence also supports the health relevance of shift-work. In a systematic review and meta-analysis, Vyas et al. (2012) reported that shift-work was associated with increased risk of myocardial infarction, ischaemic stroke, and coronary events. Similarly, Gan et al. (2015) reported an association between shift-work and increased diabetes risk, with stronger associations observed among men and rotating shift-workers. These findings are important because they establish shift-work as more than an inconvenience or scheduling preference. They position non-standard work schedules as exposures that

may contribute to chronic disease risk, although the underlying pathways are likely to be complex and not fully explained by sleep duration alone.

Functional consequences are also central to shift-work research. Fatigue, sleepiness, and impaired alertness are common concerns in shift-working populations and have implications for performance, occupational safety, and commuting risk (Caldwell et al., 2019; Mabry et al., 2022; Weaver et al., 2018). These outcomes are particularly important because they occur in real-world settings where reduced alertness may affect not only the worker, but also passengers, patients, colleagues, or the public. Shift-work may also contribute to psychosocial strain, including stress, burnout, depression, and reduced well-being, particularly in occupations with high demands, irregular schedules, and limited recovery opportunity (Giorgi et al., 2018; Kecklund & Axelsson, 2016; Wickwire et al., 2017).

Although this evidence is strong in establishing health and functional consequences, it is less precise in explaining how multidimensional sleep health is patterned within shift-working populations. Much of the literature treats shift-work as the exposure and health outcomes as the endpoint, with sleep disruption positioned as either a mechanism or associated symptom. This provides a broad occupational-health rationale, but it does not fully show which aspects of sleep health are most disrupted, whether these dimensions cluster together, or whether different work-pattern contexts produce different behavioural sleep-health profiles. CSH is useful here because it allows the sleep-related burden of shift-work to be considered as a multidimensional pattern, rather than as a single sleep deficit.

## Objective Composite Sleep Health in Shift-Working Populations

The available literature provides important foundations by showing that shift-workers experience disruption across several sleep-related outcomes, including reduced sleep duration, poorer sleep quality, sleepiness, and altered sleep timing (Kecklund & Axelsson, 2016; Vanttola et al., 2019; Wickwire et al., 2017). However, despite the well-established relationship between shift-work and disrupted sleep, research applying a

multidimensional sleep health model in shift-working populations remains limited. A smaller body of work has begun to examine sleep health multidimensionally in shift-working samples. Furihata et al. (2020) showed that poorer sleep health was associated with depressive symptoms in shift-working nurses, indicating that aggregate sleep-health scores may have relevance in shift-work populations. More recent phenotype-based work has identified multidimensional sleep-health profiles linked with job demands and work-related characteristics (Smith et al., 2024). These studies are valuable because they move beyond single sleep metrics and show that sleep-health dimensions can be considered together in working populations. However, their reliance on self-report or mixed-method sleep-health indicators means that less is known about objective behavioural-level CSH in shift-workers.

The occupational scope of existing evidence is also uneven. Nursing and healthcare samples have contributed substantially to understanding sleep disruption among shift-workers, but the sleep-health burden of shift-work may differ across industries because rosters, physical work demands, commuting patterns, recovery opportunity, and safety requirements vary. Evidence from non-healthcare occupational settings remains more limited, particularly in New Zealand.

Shift-work also presents specific measurement challenges for CSH. Sleep may occur at atypical times, across workdays and non-workdays, or in shorter recovery episodes. Field studies may account for this by combining main sleep with naps or by examining sleep in relation to specific shift types, but these decisions affect what the resulting sleep-health score represents (Vanttola et al., 2019). For objective CSH, this creates an important distinction between measuring the main sleep period and measuring total sleep across the 24-hour day. It also highlights why diary information, work schedules, and monitoring duration are important when interpreting accelerometery-derived sleep metrics in shift-workers.

Taken together, the literature supports the relevance of multidimensional sleep health in shift-working populations, but the evidence remains incomplete. Shift-work is recognised as a heterogeneous occupational exposure, and disrupted sleep is well established as part of its health burden. Less is known about how objective behavioural-level CSH varies

within shift-working contexts, how it relates to health-relevant outcomes and behaviours, and how it can be interpreted when shift-workers are analysed at different levels of classification across different research questions. This provides the basis for applying a CSH model in the present thesis as both a measurement approach and an interpretive framework for understanding sleep health in shift-working populations.

## Research Gaps

Collectively, the literature reviewed in this chapter identifies a central gap in the objective measurement and application of CSH in shift-workers. CSH frameworks have been developed through conceptual, self-report, mixed-method, and actigraphy-based approaches (Buysse, 2014; Knutson et al., 2017; Lee & Lawson, 2021; Wallace et al., 2021). However, the use of thigh-derived accelerometery to estimate the sleep metrics required for objective behavioural-level CSH remains insufficiently established, particularly within broader 24-hour movement-behaviour research. This creates a measurement issue that must be addressed before CSH can be applied confidently to the available dataset.

A second gap concerns whether objective CSH meaningfully differentiates between work-pattern contexts. Shift-work is consistently associated with disrupted sleep and adverse health outcomes (Gan et al., 2015; International Agency for Research on Cancer, 2019; Kecklund & Axelsson, 2016; Vyas et al., 2012), and field-based evidence indicates that sleep and alertness may vary across shift contexts such as morning shifts, evening shifts, night shifts, and days off (Vanttola et al., 2019; Wickwire et al., 2017). However, less is known about whether these differences are reflected in an objective multidimensional sleep health score.

A third gap concerns the relevance of objective CSH within shift-workers once the measurement and group-comparison questions have been addressed. Multidimensional sleep health has been linked with health and well-being in general and working populations (Brindle et al., 2019; Furihata et al., 2020; Griggs et al., 2023; Lee & Lawson,

2021; Makarem et al., 2022; Smith et al., 2024), but whether similar relationships are observed when CSH is measured objectively in shift-workers remains less clear. Similarly, lifestyle behaviours have often been examined in relation to individual sleep metrics (Alnawwar et al., 2023; Irish et al., 2015; Kubala et al., 2020; Skarpsno et al., 2018), while time-use research has treated sleep, sedentary behaviour, and physical activity as interdependent parts of the day (Chastin et al., 2015; Dumuid et al., 2020; 2018). In this literature, sleep is commonly represented as a single time-use compartment rather than as a multidimensional sleep-health outcome.

Together, these gaps show that objective behavioural-level CSH is conceptually promising but not yet fully established in the context required for this thesis. The literature supports the value of multidimensional sleep-health assessment, but further work is needed to determine whether the required metrics can be derived from the available accelerometery approach, whether the resulting score distinguishes meaningful work-pattern contexts, and whether it relates to health-relevant outcomes, behaviours, and 24-hour time use in shift-workers.

## Summary

This chapter has established the conceptual and methodological foundation for examining objective behavioural-level CSH in shift-workers. Sleep is biologically regulated, health-relevant, and vulnerable to disruption through multiple mechanisms, meaning that duration alone is an incomplete representation of sleep health. CSH provides a pragmatic index for summarising selected behavioural dimensions of sleep, but its interpretation depends on the dimensions selected, the measurement source, and the population under study. Accelerometery offers a feasible approach to repeated free-living measurement, although sleep remains inferred from movement and device placement must be considered carefully. Within 24-hour movement-behaviour research, sleep is usually treated as a single time-use compartment, leaving limited evidence on how daily behavioural composition relates to multidimensional sleep health. Shift-work brings these issues together because it is a heterogeneous, recurrent, and occupationally imposed

source of circadian and behavioural sleep disruption. The empirical chapters that follow apply objective behavioural-level CSH in this context by first addressing measurement feasibility, then examining its use in shift-working populations, its associations with health-relevant outcomes and behaviours, and its relationship with 24-hour time use.

# Chapter 3 – Agreement Between Wrist, Thigh, and Low-Back Accelerometery Using a Wrist-Based Algorithm

## Prelude

The previous chapter established that sleep health is increasingly understood as a multidimensional construct extending beyond sleep duration alone to include dimensions such as timing, regularity, variability, and efficiency. It also highlighted the value of objective measurement for assessing sleep in free-living settings, particularly in populations whose sleep is disrupted by irregular work schedules. In this thesis, the methodological challenge was that the sleep metrics used in later chapters needed to be derived from thigh-worn accelerometery, where measurement methods for this body location are scarce.

Now accepted for publication in Sleep Science, Chapter 3 therefore addresses this challenge by evaluating whether a wrist-based sleep measurement algorithm produces comparable sleep metrics when applied to mid-thigh and low-back accelerometer placements. This comparison was necessary to determine whether thigh-derived sleep estimates were sufficiently acceptable for use in composite sleep health (CSH) analyses. In doing so, Chapter 3 provides the measurement foundation for the later thesis studies, where objective CSH is derived from the available thigh-worn accelerometery data, and examined in relation to shift-work, health-related outcomes, and 24-hour time-use behaviours.

## Abstract

Introduction: Integrated 24-hour time-use research often benefits from accelerometer placements that capture both sleep and posture. This study evaluated whether a wrist-validated sleep algorithm applied to mid-thigh and low-back accelerometers yields sleep estimates comparable to a wrist-worn device in healthy adults.

Methods: Twenty adults wore Axivity AX3 accelerometers on the wrist, mid-thigh, and low-back during one night of sleep at home and completed a sleep diary recording bed and wake times. Data were processed in GGIR using a sustained inactivity bout algorithm guided by sleep diary information. Epoch level sleep-wake classifications and sleep metrics were derived. Repeated measures analysis of variance compared summary metrics across locations, and epoch level agreement with the wrist was quantified from confusion matrices and accuracy, sensitivity, specificity, kappa, and disagreement bouts.

Results: Epoch-level accuracy was high and similar for both the mid-thigh and low-back, with high sensitivity, moderate specificity, and disagreement concentrated in short bouts. Mean total sleep time, sleep efficiency, wake after sleep onset, awakenings, and sleep interval differed across locations, with longer sleep duration, higher efficiency, and fewer awakenings at the low-back, and mid-thigh estimates closer to the wrist.

Conclusions: Mid-thigh accelerometers yielded epoch-level classifications and sleep metrics that closely aligned with wrist-based estimates in healthy adults, whereas low-back estimates deviated more for some outcomes. Although limited by the small sample size (n=20), these findings support the potential use of mid-thigh accelerometery in 24-hour movement protocols that also require assessment of sedentary behaviour.

# Introduction

Sleep, physical activity, and sedentary behaviour collectively structure the 24-hour activity profile, profoundly influencing physical and mental health outcomes (Rosenberger et al., 2019). These behaviours are interlinked; their distribution is associated with conditions such as cardiovascular disease, obesity, diabetes, and mental health disorders (Baillot et al., 2022; Brakenridge et al., 2021; Dumuid et al., 2022a). Sleep occupies roughly one-third of the 24-hour cycle, and is critical for recovery and preparation for waking activities, while insufficient or poor-quality sleep is linked to immediate and long-term health risks (Medic et al., 2017).

Wearable accelerometers have become indispensable for objectively monitoring sleep (as well as physical activity, and sedentary behaviour) in free-living environments, offering continuous data collection over extended periods (Hills et al., 2014; Sundararajan et al., 2021). A single device that can accurately capture sleep, physical activity, and sedentary behaviours ideally minimises the number of devices worn, simplifies study procedures, improves participant comfort, and minimises disruption during free-living monitoring. Wrist-worn accelerometers are widely used for monitoring sleep due to participant compliance and the ability to detect arm movements indicative of sleep/wake states (Gao et al., 2021). However, wrist-worn devices are known to be less accurate for distinguishing lower-body postures such as sitting, standing, or lying (Gao et al., 2021; Suorsa et al., 2020). Differentiating these lower-body postures is crucial for accurately assessing sedentary behaviour, given it is defined as any waking behaviour with an energy expenditure ≤1.5 METs in a sitting, reclining, or lying posture (Tremblay et al., 2017).

The adoption of thigh-worn accelerometers is increasing in large-scale epidemiological studies where the accurate measurement of sedentary behaviour, and therefore posture detection, is a priority (Stevens et al., 2020). The Norwegian HUNT4 study represents a landmark deployment of dual-accelerometer methodology, with approximately 38,000 participants wearing accelerometers on both the thigh and lower back (Åsvold et al., 2023b). Similarly, the Prospective Physical Activity, Sitting, and Sleep (ProPASS) consortium has established an international collaboration platform specifically focused on

harmonising thigh-worn accelerometer methodologies (Stamatakis et al., 2020). These large-scale implementations demonstrate the field's recognition that thigh-worn accelerometers provide more comprehensive postural information than wrist-worn devices. However, algorithms for accurate sleep detection from the thigh remain less developed.

Recent work in thigh-worn accelerometer sleep detection shows promising but limited validation. (Johansson et al., 2023) developed a specific sleep detection algorithm for thigh-worn accelerometers, which achieved a sensitivity of 0.84 but a specificity of 0.55, indicating challenges when detecting non-sleep periods during the night. Most validated sleep algorithms are developed for the wrist, many of which are implemented in the open-source software GGIR (Karas et al., 2019; Migueles et al., 2019b). In GGIR, the widely-used (van Hees et al., 2015) algorithm operationalises sleep by first detecting periods of sustained inactivity before identifying time windows where sleep is likely to have occurred. The method for detecting periods of sustained inactivity was developed for wrist-worn accelerometers, and there is currently no evidence that this is effective for other wear locations.

This study seeks to assess whether a wrist-validated sleep algorithm, van Hees et al. (2015), can be applied to mid-thigh and low-back accelerometers in free-living, healthy adults. The two specific aims are: (1) to compare binary epoch-level sleep versus wake classifications from mid-thigh and low-back wear locations against the wrist; and (2) to compare sleep summary metrics across these wear locations, including total sleep time, wake after sleep onset, awakenings, sleep efficiency, sleep interval, and sleep onset timing. These findings could enable more comprehensive and harmonised analyses of sleep, physical activity, and sedentary behaviour for the growing number of studies using thigh- and/or back-worn accelerometers.

# Methods

## Study Design and Participants

This study utilised a cross-sectional design to compare sleep metrics derived from accelerometers placed on the mid-thigh, low-back, and wrist in healthy sleepers. Participants were recruited from the general public via advertisements and word-of-mouth. Inclusion criteria required participants to be at least 20 years old and self-report as healthy sleepers, defined as individuals not using sleep aids or devices that could affect normal sleep or mobility. Exclusion criteria included conditions or medications that could impair sleep or movement. Ethical approval was obtained (#22/300), and all participants provided written informed consent.

Sample size was determined a priori using PASS (version 15) for a within-subject repeated-measures analysis. The calculation was anchored on an interpretable and widely reported metric, total sleep time (TST). A 15-minute cross-placement difference was judged to be the smallest group-level difference worth detecting for interchangeability in free-living conditions. Relatable accelerometery studies have evaluated TST equivalence using ±10% and, more stringently, ±5%, which for an 8-hour night equal ±48 and ±24 minutes, respectively (Plekhanova et al., 2020). A 30-minute variability estimate was therefore selected as a pragmatic planning value, positioned within these published equivalence margins and intended to represent a conservative level of variation around TST estimates. With an alpha error probability of 0.05, a conservative autocorrelation among the repeated measures of 0.7, and applying the Greenhouse-Geisser correction, a sample size 20 participants achieves 81% power to detect the prespecified 15-minute cross-placement difference.

## Data Collection

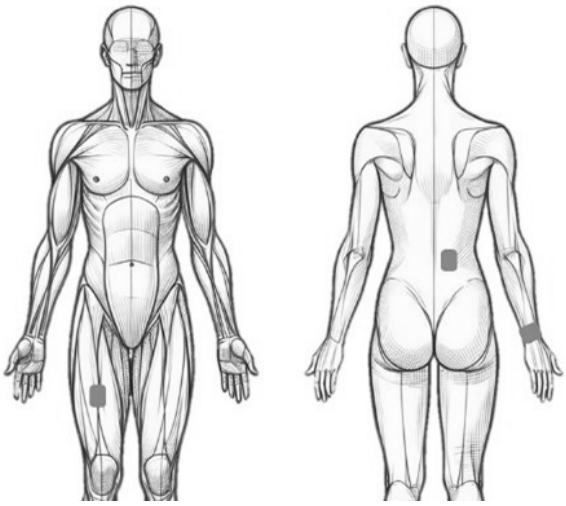
Participants wore three Axivity AX3 accelerometers simultaneously for one night of sleep in their home environment. The Axivity AX3 device is a small (23 x 32.5 x 8.9 mm; 11 g), waterproof accelerometer previously used for movement and sleep research (Johansson

et al., 2023; Narayanan et al., 2020; Plekhanova et al., 2020). Devices were configured to record at 100 Hz with a sensitivity of ±8 g, capturing data from 7:00 PM to 11:00 AM the following day. Accelerometers were placed on the right mid-anterior thigh, low-back (offset from the spine), and posterior wrist using self-adhesive pouches (mid-thigh and low-back) or a wrist strap (wrist), see Figure 3-1.

Participants received instructions to maintain their usual sleep routine, affix the devices at 6:00 PM, and remove them after waking and completing their sleep diary. Participants completed a paper-based sleep diary to record the time of device attachment and removal, bedtime, sleep attempt time, final awakening, and out-of-bed time. A single-night protocol was considered appropriate as the study aimed to compare agreement between concurrent device placements rather than characterise habitual sleep.

*Figure 3-1.*

*Placement Locations of Accelerometer Devices*



## Data Processing

Raw accelerometer data were downloaded using the OMGUI Open Movement software (version 1.0.0.30; Open Movement, Newcastle University, UK) and processed in R (R Core

Team, 2021) using the GGIR package (van Hees et al., 2025). The specific GGIR configuration parameters used in this study are provided in the supplementary configuration file in Appendix Table 1.

Briefly, sleep and wake classifications were obtained for all three devices (wrist, low-back, mid-thigh) by first applying the vanHees2015 sustained inactivity bout (SIB) algorithm (van Hees et al., 2015). A SIB was defined when the sensor's z-angle changed by no more than 5 degrees for at least 5 minutes; these are the default parameters used by GGIR when working with data from wrist-worn devices. Although it may be possible to optimise these two parameters for other body wear locations, we retained the default values for all three wear locations as an exploratory investigation of transferability.

Next, the participant sleep diary information was used as a guider to reflect the time-in-bed window. Any SIB that fully overlapped with the time-in-bed window was considered sleep. The start of the first SIB within the time-in-bed window was the sleep onset and the end of the last bout was the final wake time. Although there are methods to estimate sleep time without the use of a diary (van Hees et al., 2018), the participant sleep diary was used as the guider in this analysis to mimic a typical use case where estimating sleep is a priority.

Binary classifications (sleep, wake) for each 5-second epoch were extracted from GGIR's part-3 and part-4 milestone data. These binary data were used for epoch-level analysis. Next, the following sleep metrics were derived from the GGIR summary report: Total Sleep Time (TST) was the accumulated sleep time within the time in bed window (the GGIR *SleepDurationInSpt* variable). Wake After Sleep Onset (WASO) was computed as the length of the time in bed window, minus TST. Awakenings (AWK) were operationalised as the number of discrete wake blocks within the time in bed window (the GGIR *number_of_awakenings* variable). Sleep Efficiency (SE) was defined as the proportion of the time in bed window that was classified as sleep (the GGIR *sleepefficiency* variable). The Sleep Interval (SI) was the duration from sleep onset to final wake (the GGIR *SptDuration* variable). Lastly, Sleep Onset Timestamp (SOT) was taken directly from GGIR's *sleeponset_ts* variable.

## Statistical Analysis

Statistical analyses were conducted using jamovi (version 2.3.26). A repeated-measures analysis of variance (ANOVA) was used to compare sleep metrics (TST, WASO, AWK, SE, SI, SOT) across the three accelerometer wear locations (wrist, mid-thigh, low-back), with each metric as the dependant variable (separately) and the wear location as the independent variable. Tukey's post-hoc tests identified pairwise differences between wear locations, with these differences expressed as Cohen's d effect sizes. As the study was powered to detect differences in total sleep time (TST) between wear locations, these pairwise post-hoc comparisons should be considered exploratory. Although Tukey-adjusted post-hoc tests control the family-wise error rate, this adjustment reduces statistical power. Consequently, non-significant pairwise comparisons should not be interpreted as evidence of equivalence between wear locations. Pearson correlation coefficients were also calculated to assess the linear relationship between wrist-thigh and wrist-back sleep metrics. Finally, Bland-Altman plots were used to evaluate the limits of agreement between each pair of wear locations, for each sleep metric (Mukaka, 2012).

Next, an epoch-level analysis was performed, where the wrist data were treated as the reference. Both the lower back and mid-thigh were compared to the wrist (separately). For each participant, confusion-matrix counts were computed as true positive (both Sleep), true negative (both Wake), false positive (wrist Wake, other Sleep), and false negative (wrist Sleep, other Wake). From these counts, accuracy, sensitivity to wrist-defined Sleep, specificity to wrist-defined Wake, and Cohen's kappa were calculated. Bias in the pattern of disagreements was assessed per participant with the continuity-corrected, two-sided McNemar test. To characterise time structure of disagreements between wear locations, bout sequences of disagreement epochs were identified by run-length encoding and summarised with descriptive statistics. Bouts of awakenings greater than 3 minutes, 5 minutes, and 10 minutes in duration were also summarised.

# Results

A total of 20 individuals (40% male) aged 20–61 years (M = 37, SD = 13) consented to and completed the study. The majority of participants identified as New Zealand European (n = 18), followed by New Zealand Māori (n = 1) and Sri Lankan (n = 1). Descriptive statistics for sleep metrics recorded from each device wear location are presented in Table 3-1.

An example of minute-by-minute within-participant sleep data is shown in Figure 3-2. There were large periods of sleep alignment across all wear locations for all participants. During the sleep period, when wake events did not directly align between wear locations, it was common to observe similar lengths of wake time, just slightly offset. For example, if a wake event was recorded at 1 am on the thigh, it was common to see a similar event either just before or just after 1 am (on the wrist and/or back locations). Large discrepancies were minimal but did occur. Two participants recorded visually significant gaps in the mid-thigh and/or low-back devices in comparison to the wrist; one during the sleep period and two at the beginning of the sleep period. These can be seen in Appendix Figure 1.

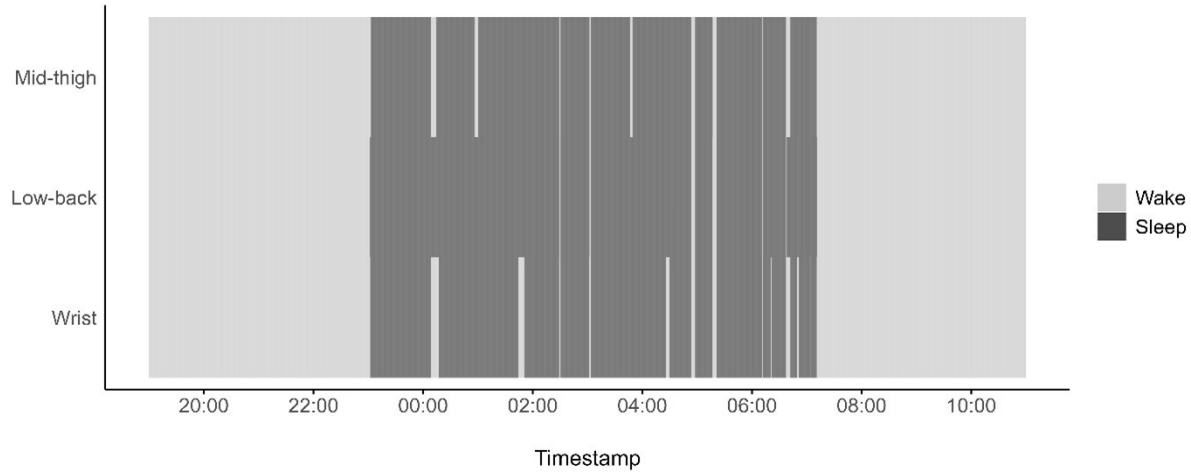
*Table 3-1.*

*Descriptive statistics for a range of sleep metrics for each device location*

| Sleep metric | N | Wrist | | | Mid-thigh | | | Low-back | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Range | Mean | SD | Range | Mean | SD | Range |
| TST, min | 20 | 403.1 | 60.6 | 204.4 | 410.0 | 60.0 | 224.6 | 425.6 | 59.3 | 203.8 |
| WASO, min | 20 | 60.6 | 31.5 | 133.9 | 56.9 | 31.6 | 115.9 | 45.8 | 26.5 | 106.3 |
| AWK, n | 20 | 17.0 | 5.7 | 24.0 | 14.6 | 5.7 | 25.0 | 13.5 | 6.1 | 25.0 |
| SI, min | 20 | 463.7 | 68.5 | 284.8 | 466.9 | 65.1 | 262.9 | 471.4 | 63.1 | 264.3 |
| SE, % | 20 | 0.87 | 0.06 | 0.22 | 0.88 | 0.06 | 0.21 | 0.90 | 0.05 | 0.20 |

*Figure 3-2.*

*Example of Minute-by-Minute Sleep Data From a Single Participant*




Across the 20 participants, both the mid-thigh and low-back closely tracked the wrist reference at the epoch level. Epoch mean accuracy was 0.89 (SD = 0.05) for the mid-thigh and 0.89 (SD = 0.06) for the low-back. Sensitivity to wrist-defined sleep was high for both wear locations (0.933 [SD = 0.05], 0.946 [SD = 0.07]). Specificity to wrist-defined wake was lower and more variable at 0.654 (SD =0.14) for the mid-thigh and 0.584 (SD = 0.16) for the low-back. Cohen's kappa showed that agreement beyond chance was moderate (mid-thigh, 0.55, SD = 0.20, low-back, 0.51, SD = 0.20). McNemar's test was significant in 17 of 20 participants for wrist vs. mid-thigh and 18 of 20 participants for wrist vs. low-back ($p < .05$), indicating a systematic imbalance in sleep versus wake epochs relative to the wrist.

The confusion matrices for the mid-thigh and low-back are shown in Figure 3-3, and disagreement bout statistics are shown in Table 3-2. On average, the mid-thigh and low-back disagreed with the wrist for 11.1 percent and 11.5 percent of the wrist Sleep Interval window, respectively. Disagreement bouts were typically short, with median bout lengths of 27.5 seconds for mid-thigh and 25 seconds for low-back. Minutes contained in wake bouts of at least 5 minutes were similar between mid-thigh and wrist, with a mean difference of 2.33 minutes. The low-back tended to record fewer such minutes than wrist, with a mean difference of -6.42 minutes. Taken together, the confusion matrices show

that true-positive and true-negative counts dominate false-positive and false-negative counts.

Figure 3-3.

Confusion Matrices for Mid-thigh and Low-back Devices

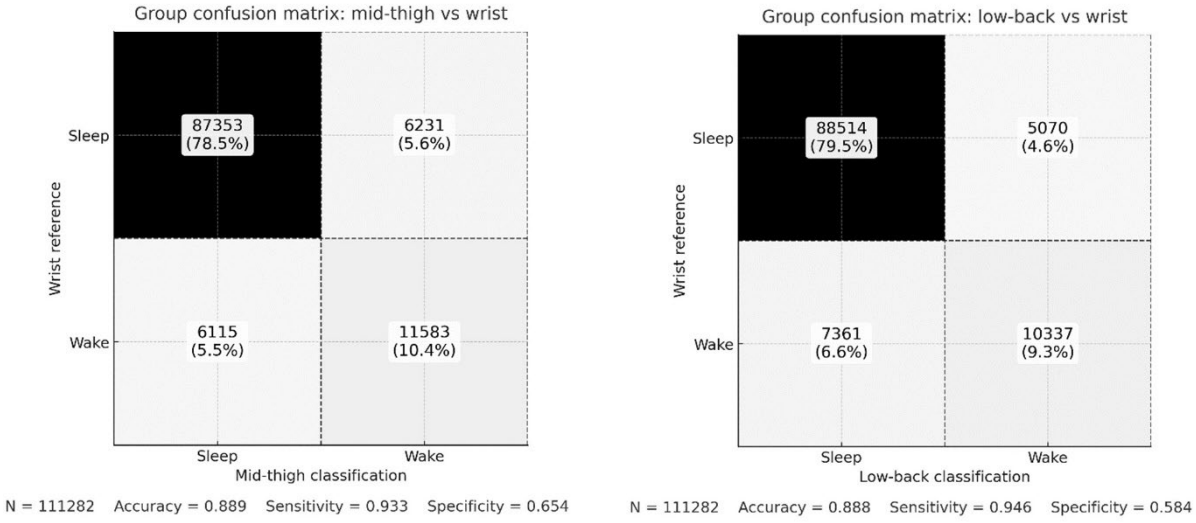



*Table 3-2.*

*Disagreement bouts: mid-thigh and low-back versus wrist*

| Outcome | Mid-thigh minus wrist | Low-back minus wrist |
|---|---|---|
| Proportion of time in disagreement, mean (SD) | 0.111 (0.051) | 0.115 (0.061) |
| Median disagreement-bout length, seconds | 27.5 | 25.0 |
| Minutes in wake bouts ≥ 3 min, mean (SD) | 2.67 (24.4) | −7.90 (29.3) |
| Minutes in wake bouts ≥ 5 min, mean (SD) | 2.33 (25.0) | −6.42 (30.3) |
| Minutes in wake bouts ≥ 10 min, mean (SD) | 4.58 (24.9) | 1.93 (31.8) |

Table 3-3 shows the repeated-measures ANOVA results, comparing sleep metrics across wear locations. Overall, the ANOVA showed a statistically significant difference among device wear locations for all sleep metrics, except SOT (p = 0.055). Post hoc comparisons are shown in Table 3-4. The largest pairwise differences emerged between the wrist and

low-back devices, particularly for TST, WASO, SE, and AWK. Fewer and smaller differences were observed between the wrist and mid-thigh, with only AWK (p = 0.007) differing by more than 2 awakenings.

*Table 3-3.*

*Repeated measures ANOVA results for each sleep metric*

| Sleep Metric | SS | df | MS | F | p |
|---|---|---|---|---|---|
| TST, min | 5297 | 2 | 2649 | 10.6 | < 0.001 |
| WASO, min | 2363 | 2 | 1181 | 6.96 | 0.003 |
| SE, % | 0.01 | 2 | 0.01 | 7.78 | 0.001 |
| AWK, count | 125 | 2 | 62.55 | 7.90 | 0.001 |
| SI, min | 598 | 2 | 299.2 | 3.39 | 0.044 |
| SOT, difference, min | 378 | 2 | 189.2 | 3.14 | 0.055 |

Differences between body locations were most pronounced for TST. Mean TST was 22.5 minutes longer with the low-back device compared to the wrist (*d* = 0.96), and 15.6 minutes longer at the low-back compared to the mid-thigh (*d* = 0.68). Differences in the number of awakenings ranged up to 3.5, with the wrist consistently showing higher counts. Mean SI varied by less than 8 minutes across all locations, while SE differed by no more than 0.03 units across all three locations.

*Table 3-4.*

*Post hoc contrasts across metrics*

| | Mid-thigh vs. Wrist | | | | | |
|---|---|---|---|---|---|---|
| Sleep Metric | MD | SE | df | t | $p_{tukey}$ | d |
| TST, min | 6.91 | 4.58 | 19.0 | 1.51 | .309 | .337 |
| WASO, min | -3.70 | 3.70 | 19.0 | -1.00 | .586 | -.224 |
| SE, % | 0.01 | 0.01 | 19.0 | 1.17 | .486 | .261 |
| AWK, count | -2.40 | 0.69 | 19.0 | -3.48 | .007 | -.778 |
| SI, min | 3.20 | 3.36 | 19.0 | 0.95 | .614 | .213 |
| SOT difference, min | -3.04 | 2.74 | 19.0 | -1.11 | .521 | -.248 |
| | Low-back vs. Wrist | | | | | |
| | MD | SE | df | t | $p_{tukey}$ | d |
| TST, min | 22.47 | 5.23 | 19.0 | 4.30 | .001 | .961 |
| WASO, min | -14.77 | 4.19 | 19.0 | -3.53 | .006 | -.788 |
| SE, % | 0.03 | 0.01 | 19.0 | 3.69 | .004 | .826 |
| AWK, count | -3.45 | 1.15 | 19.0 | -3.01 | .019 | -.673 |
| SI, min | 7.70 | 3.18 | 19.0 | 2.42 | .064 | .541 |
| SOT difference, min | -6.15 | 2.69 | 19.0 | -2.28 | .083 | -.511 |
| | Mid-thigh vs. Low-back | | | | | |
| | MD | SE | df | t | $p_{tukey}$ | D |
| TST, min | -15.56 | 5.16 | 19.0 | -3.02 | .019 | -.675 |
| WASO, min | 11.07 | 4.44 | 19.0 | 2.50 | .055 | .558 |
| SE, % | -0.02 | 0.01 | 19.0 | -2.55 | .049 | -.570 |
| AWK, count | 1.05 | 0.77 | 19.0 | 1.37 | .375 | .307 |
| SI, min | -4.50 | 2.25 | 19.0 | -2 | .140 | -.446 |
| SOT difference, min | 3.11 | 1.82 | 19.0 | 1.71 | .226 | .383 |

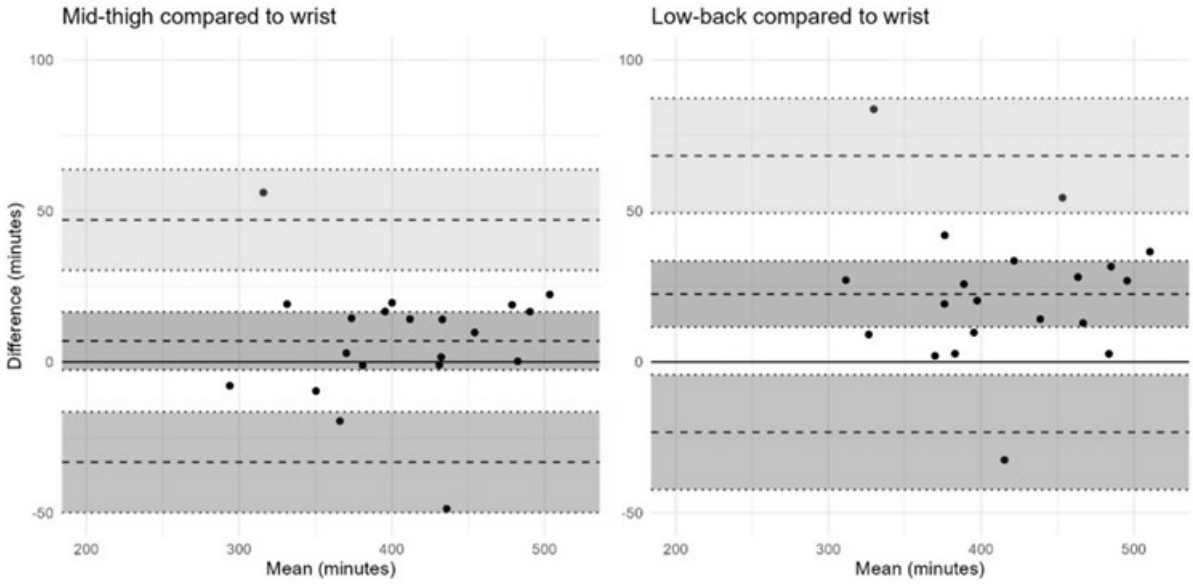
MD – mean difference, SE – standard error, df – degrees of freedom, t – paired sample t-test statistic, $p_{tukey}$ – Tukey-adjusted p-value for the post-hoc pairwise comparison, d – Cohen's effect size

Pearson correlation coefficients showed high to very high correlations between the wrist and mid-thigh wear locations across all sleep metrics (see Appendix Table 2 and Appendix Table 3). This strong correlation carried through for all sleep metrics with *r* values ranging from 0.86 to 0.98 with $p < .001$. The strongest correlation was SI, $r = 0.98$ ($p < .001$) for the wrist-thigh comparison. WASO, SE, and AWK shared the lowest correlation value at $r = 0.86$ ($p < 0.001$) for wrist-thigh comparisons. The weakest associations were found between the wrist and low-back for AWK ($r = 0.63$, $p = 0.003$) and SE ($r = 0.78$, $p < .001$).

Figure 3-4 presents Bland–Altman plots for TST, the most used sleep metric in 24-hour time-use studies. The x-axis represents the mean TST across the comparison sites, while the y-axis indicates the difference. Both the mid-thigh and low-back devices show an over estimation of TST relative to the wrist, although, the zero line was within the 95% limits of agreement for the mid-thigh. A full table of Bland-Altman results can be found in Table A-1 and Table A-2.

*Figure 3-4.*

*Bland Altman Plot for TST*



# Discussion

This study explored differences in sleep metrics and epoch-level sleep classification across wrist, mid-thigh, and low-back accelerometers. Sleep estimates were obtained using the van Hees et al. (2015) algorithm, using single-night, free-living data from healthy adults. The primary finding is that mid-thigh accelerometers produce sleep metrics (TST, WASO, AWK, SE, SI, SOT) that are comparable to those from wrist-worn devices, with strong correlations (r = 0.86–0.98) and acceptable agreement in Bland-Altman analyses, except for a slight underestimation of AWK. The discrepancy between low-back and wrist tended to be higher. At an epoch-by-epoch level, sensitivity and specificity results of the mid-thigh and low-back indicate high sensitivity (0.933, 0.946 respectively) and moderate specificity (0.654, 0.584 respectively). Taken together, these results indicate that mid-thigh estimates align closely enough with wrist metrics to support group-level summaries in healthy adults, whereas caution is required for individual-level interpretation.

Sleep algorithms for both wrist and mid-thigh wear locations have previously been compared against polysomnography (PSG); the gold-standard measure of sleep. These studies typically show a non-trivial absolute error when benchmarked against PSG; this inherent measurement error is important to acknowledge when interpreting our results. Johansson et al. (2023) reported that a thigh-based algorithm underestimated the sleep interval by 21 minutes and TST by 32 minutes (approximately 5 percent and 7 percent respectively) when compared to PSG. When developing the commonly used sustained inactivity bout thresholds for the wrist (5-degree angle, with a 5-minute window), van Hees et al. (2015) showed this overestimated TST by ~31 minutes, with an accuracy of 83 percent. Against this backdrop, our wrist-referenced estimates show that the discrepancy between mid-thigh and wrist, or low-back and wrist, is lower than the measurement error associated with the wrist itself. Thus, the agreement observed between mid-thigh or low-back and wrist-worn devices in our study falls within the established margins of error for

accelerometery-based sleep assessment relative to PSG. This result may support their interchangeable use.

The pattern of high sleep sensitivity but lower wake specificity suggest that micro-movements captured at the wrist are more often labelled as brief wake than equivalent signals at the thigh or back. In practical terms, mid-thigh and low-back appear more prone to classifying short arousals as sleep, which is consistent with the observed direction of bias in AWK, TST, and SE. This reference-dependent imbalance is not unexpected when a wrist-validated SIB approach is applied to alternative body sites. The epoch-level summaries show that most cross-placement discrepancies arose from short events rather than sustained wake, which explains close group-level alignment despite differences in brief-wake detection relative to the wrist. Optimising the 5-minute 5-degree threshold for detecting sustained activity bouts may be effective for overcoming these discrepancies in future work.

These findings indicate that existing thigh-worn datasets could possibly be re-analysed to obtain sleep metrics without new data collection, using open-source processing in GGIR. They also support the use of thigh-worn devices in 24-hour-activity protocols that seek device-based measures of both sleep, physical activity, and sedentary behaviour (Tremblay et al., 2017). Previous studies have demonstrated that combining mid-thigh and low-back accelerometers can improve the classification of waking behaviours and postures, such as sitting, standing, and lying, beyond that achievable with a single device alone (Narayanan et al., 2020). The feasibility of this approach has also been demonstrated in large-scale epidemiological studies, including the HUNT Study, in which more than 30,000 participants wore both devices concurrently to provide detailed assessments of movement behaviours across the 24-hour day (Åsvold et al., 2023a). While the present findings suggest that the thigh wear location may be suitable for deriving conventional sleep metrics, future research could explore whether combining information from both locations provides additional insights into nocturnal movement patterns and awakenings. For example, the simultaneous assessment of trunk and lower-limb movement may help identify whole-body repositioning events and isolated leg movements during sleep.

## Limitations

This study used single-night recordings in a relatively small sample and prioritised within-person differences across wrist, mid-thigh, and low-back. Consequently, some analyses, particularly those involving secondary sleep metrics and pairwise comparisons between wear locations, may have been underpowered to detect small differences. In addition, the single-night design prevented assessment of night-to-night variability and therefore may limit wider generalisability of findings. The findings of this study are also restricted to healthy sleepers and should not be generalised to individuals with sleep disorders or altered sleep physiology. While the expansion beyond one night was not feasible in the present study due to resource constraints, the results can be interpreted as a proof-of-concept that motivates multi-night replication in larger and more diverse samples with a broader range of sleep behaviours.

The free-living setting, while ecologically valid, could have introduced unknown or uncontrolled variables such as co-sleeping partners, pets, or environmental factors that may have influenced movement patterns and accelerometer data. It is also possible that measurement reactivity could have occurred given participants were required to wear three devices during their sleep period. Furthermore, as all three devices were worn simultaneously, we were unable to determine if a specific device may have caused discomfort that affected sleeping patterns.

Third, a single sleep diary to guide the algorithm across wrist, mid-thigh, and low-back devices was used. This may have reduced the independence of estimates across wear locations and introduced or contributed to correlated (timing) error. Although a diary free variant of the algorithm is available (van Hees et al., 2018), its performance for thigh and low-back wear locations in comparable conditions has not been established. Future studies should test diary-free approaches across these wear locations.

## Conclusions

In conclusion, this study provides evidence that sleep estimates derived from mid-thigh and low-back accelerometers using the van Hees algorithm, guided by sleep diary information, are broadly comparable to those derived from a wrist-worn accelerometer.

Epoch-level analyses showed that the mid-thigh captures sleep largely in line with the wrist over sustained intervals, while brief wake is detected less specifically. Overall, the mid-thigh wear location showed slightly higher accuracy for classifying different sleep metrics compared to the low-back wear location. Within the context of a sleep diary-guided implementation of the van Hees algorithm, these findings suggest that thigh-worn accelerometers may provide a practical alternative for deriving sleep metrics in studies that already use this wear location for physical activity and sedentary behaviour assessment.

# Chapter 4 – Differences in Composite Sleep Health Between Shift and Non-Shift-Workers

## Prelude

The preceding chapter established the feasibility of repurposing a wrist-validated accelerometer sleep algorithm for use on alternative body placements, demonstrating acceptable agreement between wrist- and mid-thigh-derived sleep measurements. This finding provides an important methodological foundation for the present thesis by supporting the use of mid-thigh accelerometery to derive objective sleep metrics within free-living settings. In doing so, it creates an opportunity to examine multiple dimensions of sleep simultaneously alongside other movement behaviours using a single device.

Building on this foundation, the present chapter introduces an objective approach for measuring composite sleep health (CSH) in shift-workers using accelerometer-derived sleep metrics. Specifically, this chapter applies a multidimensional CSH framework incorporating sleep regularity, timing, efficiency, duration, and variability to compare sleep health across daytime workers, shift-workers with and without night duties, and individuals with more personal than work days recorded during monitoring. Through these comparisons, the chapter provides the first empirical application of the objective CSH scoring approach used throughout this thesis and establishes the basis for subsequent chapters examining the relationships between CSH, health outcomes, behavioural factors, and 24-hour time use.

## Abstract

Introduction: Shift-work disrupts sleep through circadian misalignment and irregular sleep-wake schedules. However, most shift-work sleep research has focused on individual sleep metrics rather than multidimensional sleep health. This study examined whether objectively measured composite sleep health differed across work schedule patterns.

Methods: This cross-sectional study included employees from a national airline in the Southern Hemisphere. Participants wore thigh-mounted Axivity AX3 accelerometers continuously for approximately seven days and completed daily sleep and work logs. Sleep metrics were processed using GGIR and the van Hees sleep algorithm. Participants with at least four valid nights of sleep data were included. Composite sleep health was calculated across five objectively derived dimensions: duration, variability, efficiency, timing, and regularity. Each dimension was scored from 0–2 and summed to produce a composite sleep health score (0–10). Participants were classified as Daytime, Shifts Without Nights, Shifts With Nights, or Personal Day Dominant. Group differences were assessed using Kruskal–Wallis and Bonferroni-adjusted Mann–Whitney U tests.

Results: Of 257 recruited participants, 170 met the inclusion criteria. Daytime workers demonstrated the most favourable sleep profile, whereas shift-workers with nights demonstrated the poorest outcomes across multiple sleep dimensions. Composite sleep health differed significantly across work-pattern groups, $H(3) = 38.57$, $p < .001$. Post hoc analyses indicated that shift-workers with nights differed significantly from all other groups, while daytime workers also demonstrated significantly higher composite sleep health than shift-workers without nights.

Conclusions: Objectively measured composite sleep health differed across work schedule patterns, with night shift-work associated with the poorest multidimensional sleep health. These findings highlight the importance of assessing sleep health using multiple objective dimensions rather than relying on single sleep metrics in shift-working populations.

# Introduction

Sleep is a fundamental component of health, influencing cognitive function, emotional stability, workplace performance, and the risk of chronic conditions such as cardiovascular disease and diabetes (Hillman & Lack, 2013). In modern societies operating across a 24-hour economy, shift-work has become increasingly common, particularly within transportation and logistics industries. However, these work schedules often disrupt natural circadian rhythms and contribute to insufficient and irregular sleep (James et al., 2017). Shift-workers frequently experience circadian misalignment between biological and social time, exacerbating sleep disturbances and negatively influencing overall well-being (Roenneberg, 2023; Wittmann et al., 2006). While sleep has traditionally been evaluated through isolated outcomes such as duration, growing evidence suggests that sleep is inherently multidimensional and better understood through broader models of sleep health (Buysse, 2014; Lee & Lawson, 2021).

Buysse (2014) conceptualised sleep health as a multidimensional construct incorporating dimensions such as timing, duration, efficiency, regularity, satisfaction, and alertness. Composite sleep health approaches have since demonstrated stronger associations with health outcomes than single sleep metrics alone (Huang et al., 2021; Wallace et al., 2021). For shift-working populations, variability in sleep patterns may represent an additional important dimension due to the frequent adjustment of sleep schedules around changing work demands (Åkerstedt, 2003; Knutsson, 2003). Despite this, most research examining shift-work and sleep has focused on healthcare settings and isolated sleep outcomes, with limited attention given to multidimensional sleep health in industries such as transportation and logistics. Within New Zealand, objective comparisons of composite sleep health between shift-workers and those working traditional schedules remain sparse.

Advances in wearable accelerometer technology now enable objective assessment of sleep under free-living conditions, reducing the biases associated with self-report measures and allowing multidimensional sleep metrics to be examined simultaneously. Building on these methodological advances, this study applies an objectively derived

composite sleep health framework to compare sleep health across different working patterns. Specifically, the aims of this study were: (1) to determine whether overall composite sleep health differs across patterns of shift-work, and if so, (2) to identify which individual dimensions of composite sleep health vary between work schedule groups. Through this approach, the study seeks to contribute to the development of objective sleep health assessment methodologies and improve understanding of how occupational schedules are associated with multidimensional sleep health.

# Methods

## Participants

The data used in this study were drawn from a larger organisational research programme designed to investigate the physical, psychosocial, and occupational demands experienced by employees, including measures relating to resilience, burnout, and health behaviours. The present cross-sectional study specifically examined multidimensional sleep health among shift-workers and non-shift-workers within the same organisation.

Data collection occurred across two phases between August 2017 and April 2019. Across both phases, 257 participants were recruited (phase 1: n = 105; phase 2: n = 152). Participants were employees of a national airline operating in the Southern Hemisphere and were recruited through an internal organisational email invitation. Employees were eligible to participate if they worked within one of five selected work units: Aircraft Maintenance and Engineering, Check-In and Baggage Crew, Corporate, Customer Contact Centre, or Short-Haul Cabin Crew. These work units were identified in consultation with the organisation and approved for participation by the relevant Group Manager.

Ethical approval for each phase of the study was obtained from the Auckland University of Technology Ethics Committee (#17/109 and #18/293). All participants provided written informed consent prior to participation, including consent for deidentified data to be used in future analyses.

## Measures

### Accelerometery

Sleep metrics were derived using thigh-worn Axivity AX3 accelerometers (Axivity Ltd., Newcastle upon Tyne, UK). The AX3 is a lightweight, research-grade triaxial accelerometer that has demonstrated validity for estimating physical activity intensity and body posture in free-living settings (Rowlands et al., 2017). In addition, sleep estimates derived from the AX3 have shown acceptable agreement with other research-grade accelerometers used for sleep monitoring (Plekhanova et al., 2020). Accelerometers were configured to record continuously at a sampling frequency of 100 Hz and an acceleration range of ±8 g. Devices were initialised to capture up to 168 hours (7 days) of continuous movement data under free-living conditions. The AX3 has previously demonstrated high wear compliance in adult populations (Duncan et al., 2018).

### Sleep Diaries

Participants completed a daily sleep and activity log throughout the monitoring period. Diaries were used to record sleep onset and wake times, naps, work shifts, exercise sessions, commuting periods, and the times at which the accelerometer was attached and removed. These records were used to assist accelerometer processing and shift classification procedures.

## Procedures

Data collection was undertaken at participants' workplaces during normal working hours. Accelerometers were attached to the participant's dominant thigh using waterproof OPSITE FLEXIFIX adhesive tape (Smith & Nephew, London, UK). The attachment site was positioned at the midpoint between the hip and knee following cleaning with an alcohol wipe. A protective layer of adhesive dressing was first applied to the skin, after which the accelerometer was secured with an additional 8 × 10 cm waterproof covering to maintain placement throughout the monitoring period.

Participants were instructed to wear the accelerometer continuously for seven consecutive days, including during sleep and water-based activities such as bathing or swimming. Following completion of the monitoring period, participants removed the device themselves and returned both the accelerometer and completed diary using the provided packaging.

Demographic information including age, gender, and ethnicity was collected through an online self-report survey completed during participant onboarding. Although additional survey measures were collected as part of the broader research programme, only the variables relevant to the present study were included in the current analyses.

## Data Processing

### Accelerometer Processing

Accelerometer data were downloaded using OMGUI software (Open Movement, Newcastle University, Newcastle upon Tyne, UK) and exported as raw .CWA files linked to each participant's unique identification number. Raw accelerometer files were batch processed using the GGIR package in R (Migueles et al., 2019a). Sleep metrics were derived using the van Hees sleep detection algorithm implemented within GGIR (van Hees et al., 2015). This algorithm used accelerometer movement patterns in combination with participant sleep diary information to estimate sleep periods. The specific GGIR configuration parameters used in this study are provided in the supplementary configuration file in Appendix Table 1.

The van Hees algorithm was originally developed for wrist-worn accelerometers (van Hees et al., 2015); however, recent work within this thesis demonstrated acceptable agreement between wrist- and mid-thigh-derived sleep estimates when applied to thigh-mounted devices (Chapter 3). Sleep metrics derived from the accelerometer data included sleep onset time, wake time, total sleep time, sleep midpoint, and sleep efficiency.

Only participants who recorded a minimum of four nights of valid sleep data were retained for analysis (Migueles et al., 2017). Traditional weekday and weekend criteria

were not applied due to the predominantly shift-working nature of the cohort and the irregularity of work schedules.

Shift Classification

Hard-copy sleep and activity diaries were manually entered into Microsoft Excel, with all entries independently checked for accuracy by a second researcher. Work shifts were classified according to the framework proposed by Vanttola et al. (2019), based on participants' reported work start and finish times. Shifts were categorised as:

1. Early Morning Shift: shifts commencing between 03:00 and 05:59 and finishing no later than 18:00 on the same day.
2. Day Shift: shifts commencing at or after 06:00 and finishing no later than 18:00 on the same day.
3. Evening Shift: shifts involving work between 18:00 and 23:00 that did not meet night-shift criteria and finished on the same day.
4. Night Shift: shifts including at least three hours of work between 23:00 and 07:00, or shifts crossing midnight into the following day.
5. Personal Day: days where no shift-work was recorded.

Participants were subsequently grouped into one of four work-pattern categories based on the dominant pattern of work recorded during the monitoring period. Participants in work-dominant categories were required to have recorded more workdays than personal days during the monitoring week. The four work-pattern categories were:

- Daytime Workers: participants who recorded only day shifts.
- Shift-workers Without Nights: participants who recorded combinations of shift types excluding night shifts.
- Shift-workers With Nights: participants who recorded at least one night shift alongside any combination of other shift types.
- Personal Day Dominant: participants who recorded more personal days than workdays during the monitoring period, regardless of shift type worked.

Composite Sleep Health Construction

Composite sleep health (CSH) was operationalised using an adapted version of the Ru-SATED framework proposed by Buysse (2014). The original Ru-SATED model incorporates dimensions of sleep regularity, satisfaction, alertness, timing, efficiency, and duration (Brandolim Becker et al., 2018; Buysse, 2014; Lee & Lawson, 2021). For the present study, the model was adapted to focus specifically on objectively derived sleep measures relevant to shift-working populations.

The subjective dimensions of sleep satisfaction and alertness were excluded because the present study focused on accelerometer-derived sleep metrics, and these dimensions are inherently perception-based and less consistently operationalised across studies (Krystal & Edinger, 2008; Ohayon et al., 2017). In contrast, sleep variability was incorporated as an additional dimension due to its particular relevance to shift-workers, whose sleep schedules frequently fluctuate in response to changing work demands (Åkerstedt, 2003; Wickwire et al., 2017).

Five dimensions of sleep health were therefore included in the composite model: duration, variability, timing, regularity, and efficiency. The selected metrics were derived from the accelerometer data processed using the van Hees algorithm and were chosen based on both availability within the dataset and relevance to shift-working populations. The metrics used were:

- Duration: mean total sleep time across all recorded sleep periods.
- Variability: coefficient of variation of total sleep time.
- Timing: mean sleep midpoint.
- Regularity: standard deviation of sleep midpoint.
- Efficiency: mean sleep efficiency across recorded sleep periods.

Composite sleep health scores were calculated by summing scores across the five sleep dimensions. Each dimension was assigned a score of 0 (poor), 1 (sub-optimal/moderate),

or 2 (optimal), resulting in a total possible composite sleep health score ranging from 0 to 10.

Where established recommendations existed, threshold values were derived from published literature and public health guidelines. In the absence of established thresholds for objectively derived multidimensional sleep health in shift-working populations, remaining cut-points were informed through expert discussion and iterative synthesis of the literature. Thresholds, scoring criteria, and supporting rationales for each sleep dimension are presented in Table 4-1.

*Table 4-1.*

*Composite Sleep Health dimensions, metrics, thresholds, and rationales*

| Dimension | Metric | Threshold | | | Threshold rationale |
|---|---|---|---|---|---|
| | | Optimal (2) | Moderate (1) | Poor (0) | |
| Duration | Mean total sleep time | 7–9 h | 6–7 h or 9–9.5 h | <6 h or >9.5 h | Based on the joint consensus statement for healthy adult sleep duration, which recommends 7–9 hours of sleep per night for optimal health and functioning (Watson et al., 2015). |
| Variability | Coefficient of variation of total sleep time | ≤ 11.1% | 11.1%–16.3% | >16.3% | Derived from sample-based quintiles of sleep duration variability. Cut-points were further informed through exploratory comparisons with Brief Resilience Scale and Sleeping Troubles scores, supporting lower variability as indicative of more favourable sleep health. |
| Timing | Mean sleep midpoint | 2:00–4:00 AM | 1:30–2:00 AM or 4:00–4:30 AM | <1:30 AM or >4:30 AM | Informed by circadian rhythm and chronobiology literature identifying a sleep midpoint between 02:00 and 04:00 as broadly reflective of healthy circadian alignment in adult populations (Furihata et al., 2017; Roenneberg et al., 2007). |
| Regularity | SD of sleep midpoint | ≤30 min | 30–60 min | >60 min | Informed by sleep regularity research demonstrating that greater variability in sleep timing is associated with increased cardiometabolic and cardiovascular risk. A standard deviation exceeding 60 minutes was considered indicative of poor sleep regularity (Sletten et al., 2023). |
| Efficiency | Mean sleep efficiency | ≥85% | 75–84.9% | <75% | Based on National Sleep Foundation recommendations for healthy adult sleep efficiency, where values ≥85% are considered indicative of good sleep quality (Ohayon et al., 2017). |

### Statistical Analysis

All statistical analyses were conducted using IBM SPSS Statistics (Version 29; IBM Corp., Armonk, NY, USA) (IBM Corp., 2022, 2023). Participant characteristics and sleep health variables were summarised using descriptive statistics. Categorical variables were reported as counts and percentages, while continuous variables were reported as mean and standard deviation (SD) or median and interquartile range (IQR), depending on data distribution.

Non-parametric analyses were selected due to the ordinal structure and non-normal distribution of composite sleep health scores. To address Aim 1, differences in composite sleep health scores between work-pattern groups were examined using a Kruskal–Wallis test. Composite sleep health score (range 0–10) was treated as the dependent variable, while work-pattern group (Daytime Workers, Shift-workers Without Nights, Shift-workers With Nights, and Personal Day Dominant) was treated as the independent variable. Where omnibus tests were statistically significant, post-hoc Mann–Whitney U tests with Bonferroni-adjusted p-values were conducted to identify pairwise group differences.

To address Aim 2, this analytical process was repeated separately for each individual sleep health dimension (Duration, Variability, Timing, Regularity, and Efficiency; each range 0–2) to determine which dimensions contributed to differences in overall composite sleep health between work-pattern groups.

## Results

### Participant characteristics

Of the 257 participants recruited for the broader study, 170 met the inclusion criteria for the present analysis by recording a minimum of four nights of valid sleep data from the thigh-worn accelerometers. Participant characteristics are presented in Table 4-2. The sample was relatively balanced by gender, comprising 81 men (48%) and 89 women (52%), and included participants across a broad adult age range. Participants represented a culturally diverse cohort, with the majority identifying as European or other ethnicity.

Māori and Pacific participants represented approximately 8% and 11% of the sample, respectively.

*Table 4-2.*

*Participant Characteristics*

| Variable | Sub-variable | Count | % of sample (170) |
|---|---|---|---|
| Gender | Male | 81 | 48 |
| | Female | 89 | 52 |
| Shift Type | Daytime (no shifts) | 44 | 26 |
| | Shifts Without Nights | 88 | 52 |
| | Shifts With Nights | 25 | 15 |
| | Personal Day Dominant | 13 | 8 |
| Age | < 30 years | 33 | 19 |
| | 30-39 years | 45 | 26 |
| | 40-49 years | 43 | 25 |
| | 50-59 years | 25 | 15 |
| | 60+ years | 20 | 12 |
| | Undisclosed | 4 | 2 |
| Ethnicity † | Māori | 13 | 8 |
| | Pacific | 19 | 11 |
| | Asian | 19 | 11 |
| | MELAA* | 22 | 13 |
| | European and other | 126 | 74 |

* Middle Eastern, Latin American, African; † Ethnicity total count exceeds 170 as participants were permitted to select multiple ethnicities.

## Sleep Metrics Across Work-Pattern Groups

Mean values and standard deviations for each sleep metric across work-pattern groups are presented in Table 4-3. Across all dimensions, daytime workers recorded more favourable sleep metrics than other work-pattern groups, while the Shifts With Nights group recorded the least favourable values. Daytime workers recorded the longest mean

total sleep time (6.15 h), the lowest variability in sleep duration (CV TST = 15.8%), the highest sleep efficiency (76.8%), and the greatest sleep regularity (SD midpoint = 0.69 h). In contrast, the Shifts With Nights group demonstrated the shortest sleep duration (5.02 h), lowest sleep efficiency (66.7%), and greatest irregularity in sleep timing (SD midpoint = 2.12 h). This group was also the only work-pattern group with an average sleep midpoint occurring outside the optimal 02:00–04:00 window, with a mean midpoint of 04:34. Greater variability in total sleep time was observed among both the Personal Day Dominant and Shifts With Nights groups, indicating more inconsistent sleep patterns within these participants.

*Table 4-3.*

*Sleep Dimension Means and Standard Deviations*

| Dimension | Total | Daytime | Shifts Without Nights | Shifts With Nights | Personal Day Dominant |
|---|---|---|---|---|---|
| Value (expressed as) | | | Mean (standard deviation) | | |
| Duration (h) | 5.73 (1.18) | 6.15 (.899) | 5.78 (1.15) | 5.02 (1.25) | 5.35 (1.46) |
| Variability (CV%) | 21.9 (11.8) | 15.8 (7.21) | 21.3 (11.0) | 29.4 (13.0) | 31.8 (13.2) |
| Efficiency (percentage) | 73.2 (9.0) | 76.8 (7.7) | 73.7 (8.3) | 66.7 (9.6) | 70.4 (9.7) |
| Timing (hh:mm) | 3:01 (1:17) | 2:34 (0:45) | 2:50 (1:06) | 4:34 (1:35) | 2:54 (1:11) |
| Regularity (h) | 1.28 (.97) | 0.685 (.391) | 1.21 (.668) | 2.12 (1.75) | 1.53 (1.11) |

Distribution of Sleep Dimension Scores

The distribution of sleep dimension scores across work-pattern groups is presented in Table 4-4. Across nearly all sleep dimensions, shift-workers undertaking night shifts demonstrated a greater proportion of poor scores (score = 0) compared with other

groups. This pattern was particularly evident for duration, where 84% of participants in the Shifts With Nights group were classified within the poor category, compared with 34.1% of daytime workers. Similarly, poor sleep efficiency scores were observed in 84% of night shift-workers, compared with 31.8% of daytime workers.

*Table 4-4.*

*Distribution of Sleep Dimension Scores Across Shift Groups*

| Dimension | Score | Daytime | Shifts Without Nights | Shifts With Nights | Personal Day Dominant | Total participants per threshold |
|---|---|---|---|---|---|---|
| Duration | 0 | 15 (34.1%) | 47 (53.4%) | 21 (84.0%) | 8 (61.5%) | 91 (53.5%) |
| | 1 | 25 (56.8%) | 27 (30.7%) | 2 (8.0%) | 3 (23.1%) | 57 (33.5%) |
| | 2 | 4 (9.1%) | 14 (15.9%) | 2 (8.0%) | 2 (15.4%) | 22 (12.9%) |
| Variability | 0 | 20 (45.5%) | 51 (58.0%) | 22 (88.0%) | 12 (92.3%) | 105 (61.8%) |
| | 1 | 10 (22.7%) | 24 (27.3%) | 3 (12.0%) | 0 (0.0%) | 37 (21.8%) |
| | 2 | 14 (31.8%) | 13 (14.8%) | 0 (0.0%) | 1 (7.7%) | 28 (16.5%) |
| Efficiency | 0 | 14 (31.8%) | 45 (51.1%) | 21 (84.0%) | 8 (61.5%) | 88 (51.8%) |
| | 1 | 24 (54.5%) | 40 (45.5%) | 4 (16.0%) | 3 (23.1%) | 71 (41.8%) |
| | 2 | 6 (13.6%) | 3 (3.4%) | 0 (0.0%) | 2 (15.4%) | 11 (6.5%) |
| Timing | 0 | 2 (4.5%) | 14 (15.9%) | 13 (52.0%) | 1 (7.7%) | 30 (17.6%) |
| | 1 | 9 (20.5%) | 15 (17.0%) | 4 (16.0%) | 3 (23.1%) | 31 (18.2%) |
| | 2 | 33 (75.0%) | 59 (67.0%) | 8 (32.0%) | 9 (69.2%) | 109 (64.1%) |
| Regularity | 0 | 13 (29.5%) | 51 (58.0%) | 19 (76.0%) | 9 (69.2%) | 92 (54.1%) |
| | 1 | 24 (54.5%) | 27 (30.7%) | 6 (24.0%) | 3 (23.1%) | 60 (35.3%) |
| | 2 | 7 (15.9%) | 10 (11.4%) | 0 (0.0%) | 1 (7.7%) | 18 (10.6%) |
| Total participants per group | | 44 | 88 | 25 | 13 | 170 (100%) |

## Composite Sleep Health Scores

Median composite sleep health scores and dimension-specific scores for each work-pattern group are presented in Table 4-5. Overall, daytime workers demonstrated the most favourable composite sleep health profile, recording the highest median composite score (median = 4, IQR = 1). In contrast, the Shifts With Nights and Personal Day Dominant groups demonstrated the poorest overall sleep health, each recording median composite scores of 0. Median scores for Duration, Variability, Efficiency, and Regularity were highest among daytime workers, whereas the Shifts With Nights group generally recorded the lowest scores. Across the cohort, median composite sleep health scores were low relative to the maximum possible score of 10.

*Table 4-5.*

*Median (IQR) composite sleep health dimension scores by work-pattern group*

| Dimension | Daytime | Shifts Without Nights | Shifts With Nights | Personal Day Dominant | Total |
|---|---|---|---|---|---|
| Duration | 1 (1) | 0 (1) | 0 (0) | 0 (1) | 0 (1) |
| Variability | 1 (2) | 0 (1) | 0 (0) | 0 (0) | 0 (1) |
| Efficiency | 1 (1) | 0 (1) | 0 (0) | 0 (1) | 0 (1) |
| Timing | 2 (1) | 2 (1) | 0 (2) | 2 (1) | 2 (1) |
| Regularity | 1 (0) | 0 (1) | 0 (1) | 0 (1) | 1 (1) |
| Composite total | 4 (1) | 3 (3) | 0 (0) | 0 (1) | 3 (4) |

Median (Interquartile range, IQR)

## Differences in Composite Sleep Health Between Work-Pattern Groups

Kruskal–Wallis analysis identified significant differences in overall composite sleep health scores between work-pattern groups, $H(3) = 38.57$, $p < .001$. Post-hoc pairwise comparisons were conducted using Bonferroni-adjusted Mann–Whitney U tests, with effect sizes calculated as $r = z/\sqrt{N}$.

The Shifts With Nights group demonstrated significantly lower composite sleep health scores than both the Shifts Without Nights group ($z = -4.35$, adjusted $p < .001$, $r = .41$) and the Daytime group ($z = -6.15$, adjusted $p < .001$, $r = .74$). A significant difference was also observed between the Daytime and Shifts Without Nights groups ($z = -3.01$, adjusted $p = .016$, $r = .36$).

No statistically significant differences were observed between the Shifts With Nights and Personal Day Dominant groups ($z = -2.16$, adjusted $p = .185$, $r = .35$), the Personal Day Dominant and Shifts Without Nights groups ($z = 0.83$, adjusted $p = 1.000$, $r = .08$), or the Personal Day Dominant and Daytime groups ($z = 2.54$, adjusted $p = .066$, $r = .34$).

## Differences Across Individual Sleep Dimensions

Kruskal–Wallis analyses identified significant differences between work-pattern groups across all five sleep dimensions examined, including duration ($H(3) = 11.64$, $p = .009$), variability ($H(3) = 19.10$, $p < .001$), efficiency ($H(3) = 18.75$, $p < .001$), timing ($H(3) = 19.50$, $p < .001$), and regularity ($H(3) = 16.79$, $p < .001$).

Post-hoc pairwise comparisons using Bonferroni-adjusted Mann–Whitney U tests indicated that participants in the Shifts With Nights group consistently demonstrated poorer sleep outcomes than other work-pattern groups across multiple sleep dimensions. Compared with daytime workers, the Shifts With Nights group demonstrated significantly shorter sleep duration ($z = 3.38$, adjusted $p = .004$, $r = .41$), greater sleep variability ($z = 3.80$, adjusted $p = .001$, $r = .46$), poorer sleep efficiency ($z = 4.30$, adjusted $p < .001$, $r = .52$), later sleep midpoint timing ($z = 4.25$, adjusted $p < .001$, $r = .51$), and poorer sleep regularity ($z = 3.77$, adjusted $p = .001$, $r = .45$).

Compared with the Shifts Without Nights group, the Shifts With Nights group also demonstrated significantly greater variability ($z = 2.71$, adjusted $p = .041$, $r = .25$), poorer sleep efficiency ($z = 2.78$, adjusted $p = .033$, $r = .26$), and later sleep midpoint timing ($z = 3.74$, adjusted $p = .001$, $r = .35$). No significant differences between these groups were observed for duration or regularity following Bonferroni correction.

Additional pairwise differences were identified between daytime workers and other work-pattern groups. Daytime workers demonstrated significantly lower sleep variability than the Personal Day Dominant group ($z = 3.06$, adjusted $p = .013$, $r = .41$), and significantly greater sleep regularity than the Shifts Without Nights group ($z = 2.88$, adjusted $p = .024$, $r = .25$). No other pairwise comparisons reached statistical significance following Bonferroni adjustment. Full post-hoc comparison statistics are presented in Table 4-6.

*Table 4-6.*

*Bonferroni-adjusted post-hoc pairwise comparisons for individual sleep dimensions*

| Dimension | Comparison | z | $p_{adj}$ | *r* |
|---|---|---|---|---|
| Duration | Shifts With Nights vs Daytime | 3.38 | .004 | .41 |
| Variability | Shifts With Nights vs Daytime | 3.80 | .001 | .46 |
| | Shifts With Nights vs Shifts Without Nights | 2.71 | .041 | .25 |
| | Personal Day Dominant vs Daytime | 3.06 | .013 | .41 |
| Efficiency | Shifts With Nights vs Daytime | 4.30 | < .001 | .52 |
| | Shifts With Nights vs Shifts Without Nights | 2.78 | .033 | .26 |
| Timing | Shifts With Nights vs Daytime | 4.25 | < .001 | .51 |
| | Shifts With Nights vs Shifts Without Nights | 3.74 | .001 | .35 |
| | Shifts With Nights vs Personal Day Dominant | 2.76 | .034 | .45 |
| Regularity | Shifts With Nights vs Daytime | 3.77 | .001 | .45 |
| | Shifts Without Nights vs Daytime | 2.88 | .024 | .25 |

Only statistically significant pairwise comparisons following Bonferroni adjustment are shown. Effect sizes calculated as $r=z/\sqrt{N}$

## Discussion

This study examined multidimensional sleep health across different work-pattern groups using objectively derived sleep metrics. The findings demonstrated that composite sleep health differed significantly across work schedules, thereby addressing the first aim of the

study. Additionally, statistically significant differences were observed across each of the five individual sleep dimensions — duration, variability, efficiency, timing, and regularity — addressing the second aim. Collectively, these findings reinforce the growing understanding that sleep health is strongly influenced by work schedule structure and circadian stability, particularly where schedules disrupt consistent sleep-wake routines.

Night shift-workers consistently demonstrated the poorest multidimensional sleep health profile. Compared with daytime workers, participants undertaking night shifts recorded shorter sleep duration, poorer sleep efficiency, greater variability in sleep duration, and later sleep timing. These findings demonstrate that differences in overall composite sleep health were driven by disruptions across multiple sleep dimensions rather than a single isolated sleep metric. The findings align with previous research demonstrating that night shift-work disrupts circadian alignment and impairs sleep quality (Chang & Peng, 2021; Shin et al., 2021; Wickwire et al., 2017). While the present study did not directly measure metrics such as wake after sleep onset or sleep-onset latency, the multidimensional framework used here captured related aspects of sleep disruption through efficiency, timing, and regularity measures. This supports previous work by Wallace et al. (2021), who demonstrated that conceptually related sleep metrics within the same domain often provide comparable predictive value for health outcomes. Together, these findings reinforce the utility of composite sleep health approaches for understanding sleep in occupational settings, particularly where sleep disruption occurs across multiple dimensions simultaneously.

A notable finding arising from the first aim of the study was that poorer sleep health was not limited exclusively to night shift-workers. Participants classified as Shifts Without Nights also demonstrated poorer composite sleep health than daytime workers, despite not undertaking overnight work. Although these participants generally demonstrated more favourable sleep profiles than the Shifts With Nights group, they still exhibited poorer sleep regularity than daytime workers, alongside trends toward greater variability and lower efficiency. This suggests that irregular scheduling itself, even in the absence of night work, may negatively influence multidimensional sleep health. Previous research has similarly identified that rotating and inconsistent schedules can contribute to

circadian disruption and impaired sleep outcomes independent of overnight work demands (Chang & Peng, 2021; Härmä et al., 2019). The findings suggest that night shift-work may contribute to broad multidimensional sleep disruption, whereas irregular scheduling without night work may preferentially affect sleep stability and regularity.

The findings relating to the Personal Day Dominant group were particularly noteworthy. Although relatively few statistically significant pairwise differences were observed involving this group, participants demonstrated high sleep variability and irregularity descriptively, with variability significantly greater than that observed among daytime workers. These findings suggest that instability in sleep duration, efficiency, and regularity may persist even where sleep timing remains relatively aligned. One possible explanation for these findings is social jetlag, where behavioural and social routines become misaligned with biological sleep-wake rhythms (Roenneberg, 2023). Previous work has shown that irregular daily schedules and fluctuating time-use patterns may contribute to disrupted sleep cycles and poorer sleep outcomes (Kolbe-Alexander et al., 2019). The present findings extend this understanding by suggesting that irregularity itself, rather than night work alone, may represent an important determinant of multidimensional sleep health.

The importance of sleep variability and regularity emerged as a central finding of this study. While sleep duration is often the most commonly reported sleep outcome in occupational health research, the present findings demonstrate that instability in sleep timing and duration may be equally important when evaluating overall sleep health. Participants with greater sleep variability and less stable sleep timing generally demonstrated poorer composite sleep health scores, regardless of whether this instability arose from shift-work schedules or irregular personal routines. These findings highlight the importance of examining multiple dimensions of sleep when evaluating differences in sleep health between work-pattern groups. They also support growing evidence that multidimensional sleep health frameworks may provide a more comprehensive understanding of sleep-related health risk than single sleep metrics alone (Buysse, 2014; Lee & Lawson, 2021). Evaluating sleep exclusively through duration may therefore

overlook important disruptions in timing, efficiency, and regularity that collectively influence restorative sleep and broader health outcomes.

A key contribution of this study was the operationalisation of an objective multidimensional sleep health framework using accelerometer-derived sleep metrics. While previous multidimensional sleep health research has frequently relied on self-report questionnaires or subjective sleep measures, the present study applied an adapted composite sleep health approach using objectively measured sleep data collected under free-living conditions. The adaptation of the Ru-SATED framework to include sleep variability and remove subjective domains allowed the model to better reflect the challenges experienced within shift-working populations. Additionally, the use of thigh-worn accelerometery demonstrates the feasibility of deriving multidimensional sleep health metrics from a single device capable of simultaneously capturing sleep and movement behaviours. This provides important methodological opportunities for future research examining the interaction between sleep, physical activity, sedentary behaviour, and broader 24-hour time use.

Despite these strengths, several limitations should be acknowledged. The cross-sectional design limited the ability to determine temporal or causal relationships between work schedules and sleep health. Longitudinal research is needed to examine how multidimensional sleep health changes over time in response to occupational demands and schedule variability. Additionally, subjective dimensions of sleep health, such as sleep satisfaction and daytime alertness, were not included in the present study. Although the focus on objective sleep measures was intentional, integrating subjective and objective measures may provide a more comprehensive understanding of sleep health among shift-working populations (Härmä et al., 2019). Finally, several potentially important confounding factors were not assessed, including workload, commuting time, sleep or alertness aids, and physical activity behaviours. These factors may influence sleep health and should be considered in future research.

Overall, the findings of this study demonstrated significant differences in multidimensional sleep health across work-pattern groups, thereby addressing the first aim of the study, with night shift-workers exhibiting the poorest overall sleep profiles.

Differences across individual dimensions of sleep health further addressed the second aim by demonstrating that work schedules influence multiple aspects of sleep simultaneously. Poor sleep health was also evident among workers with irregular schedules that did not include night shifts, particularly for sleep regularity, while participants with more personal than work days demonstrated elevated sleep variability and instability in sleep timing. These findings suggest that instability in daily routines and sleep-wake patterns may represent a broader contributor to poor sleep health beyond night work alone. The present study supports the use of multidimensional and objectively derived sleep health frameworks for understanding the complex relationships between occupational schedules and sleep health in free-living populations.

# Chapter 5 – The Association Between Composite Sleep Health and Health and Well-being Outcomes in Shift-Workers

## Prelude

The preceding chapter applied an objective composite sleep health (CSH) framework to examine whether multidimensional sleep health differed across work schedule patterns. The findings demonstrated that CSH was not evenly distributed across groups, with shift-workers who worked nights displaying the poorest overall sleep health profile across several dimensions, including duration, variability, efficiency, timing, and regularity. While these findings established that objectively measured CSH can distinguish between groups exposed to different working schedules, they did not determine whether poorer sleep health was associated with broader health and well-being outcomes. For the present thesis, this distinction is important because if CSH is to provide a meaningful multidimensional assessment of sleep in shift-workers, it must also relate to indicators of psychological health and perceived well-being.

Accordingly, this chapter examines the association between objectively measured composite sleep health and self-reported psychosocial and health-related outcomes in shift-workers. Specifically, it investigates whether CSH is associated with resilience, perceived stress, burnout, depressive symptoms, general health, and subjective sleeping troubles. In doing so, the chapter utilises data collected from Phase 2 of the original corpus data collection and extends the previous group-comparison analysis toward evaluating the broader relevance of objective CSH. This also provides a conceptual bridge to the subsequent chapters examining behavioural correlates and 24-hour time-use patterns associated with composite sleep health in shift-workers.

# Abstract

Introduction: Shift-workers are vulnerable to disrupted sleep due to irregular schedules that conflict with circadian rhythms. Although sleep is increasingly conceptualised as a multidimensional construct, limited research has examined whether objectively measured composite sleep health is associated with psychosocial and health-related outcomes in shift-workers. This study aimed to determine the association between objectively measured composite sleep health and self-reported resilience, stress, burnout, depressive symptoms, general health, and sleeping troubles in shift-workers.

Methods: This cross-sectional observational study used secondary data from employees of a national airline in the Southern Hemisphere. Participants were included if they recorded at least one work shift commencing before 06:00 or ending after 18:00 and provided at least four nights of sleep data. Sleep was measured over seven consecutive days using Axivity AX3 accelerometers and daily sleep logs. Sleep metrics were processed using GGIR and the van Hees algorithm. Composite sleep health scores were calculated from five objectively measured dimensions: duration, variability, timing, regularity, and efficiency. Self-reported outcomes were assessed using the Brief Resilience Scale and selected Copenhagen Psychosocial Questionnaire II subscales. Separate linear regression models examined associations between composite sleep health and each outcome.

Results: Eighty-nine shift-workers met the inclusion criteria, with 88 completing the survey measures. The mean composite sleep health score was 2.93 ± 2.06. Composite sleep health was not significantly associated with resilience, general health, burnout, perceived stress, depressive symptoms, somatic stress, or cognitive stress. The association with subjective sleeping troubles approached statistical significance (B = -2.064 , SE = 1.202, 95% CI: -4.454 to 0.326, p = 0.09), although explanatory power remained low ($R^2$ = 0.033).

Conclusions: Objectively measured composite sleep health demonstrated limited explanatory value for psychosocial and health-related outcomes in shift-workers. These

findings suggest that objective and subjective sleep constructs may capture different aspects of the sleep–health relationship in shift-working populations.

# Introduction

Sleep is a fundamental biological process that restores the body physically while also playing a critical role in mental and emotional well-being. Traditionally, sleep research has focused on singular aspects of sleep such as total sleep time or sleep quality. For example, a large-scale study in New Zealand found that short sleep duration was associated with increased depressive symptoms and poorer self-rated health (Lee & Sibley, 2019). Both sleep quantity and quality influence multiple aspects of psychosocial functioning (Paine et al., 2019). More recent frameworks, however, conceptualise sleep as a multidimensional construct referred to as "sleep health." Originally proposed by Buysse (2014), this perspective incorporates several interrelated dimensions including regularity, satisfaction, timing, duration, efficiency, and daytime alertness. Rather than focusing solely on the presence or absence of sleep disorders, this approach evaluates sleep along a continuum from optimal to suboptimal functioning, reflecting broader definitions of health that emphasise well-being in addition to disease absence (Buysse, 2014; Ravyts et al., 2021). By integrating multiple dimensions, composite sleep health frameworks provide a more comprehensive understanding of how sleep contributes to overall health and functioning.

Insufficient or disrupted sleep has been associated with a range of physiological and psychological conditions that impair overall health and well-being (Cappuccio et al., 2010; Cedernaes et al., 2015; Furihata et al., 2017; Lee & Lawson, 2021; Medic et al., 2017; Russell & Lightman, 2019; Tempesta et al., 2020). Sleep disruption has been linked to heightened stress responses, inflammation, metabolic dysregulation, mood disturbance, and cognitive impairment (Chattu et al., 2018a; Russell & Lightman, 2019). These effects may occur both acutely and chronically, contributing to a substantial public health burden (Medic et al., 2017; WHO, 2004). Shift-workers are particularly vulnerable because irregular work schedules frequently conflict with natural circadian rhythms, resulting in chronic sleep disruption and increased risk of adverse physical and psychological health outcomes (Kecklund & Axelsson, 2016). Beyond physical health risks, disrupted sleep among shift-workers has been associated with impaired emotional regulation, reduced psychological resilience, and increased susceptibility to stress, burnout, anxiety, and

depressive symptoms (Haack & Mullington, 2005; Tempesta et al., 2020). Supporting this, Furihata et al. (2020) found that poorer composite sleep health was associated with greater depressive symptoms among shift-working nurses, highlighting the importance of multidimensional sleep assessment in shift-working populations.

Despite growing interest in composite sleep health, little is known about how objectively measured composite sleep health relates to broader health and well-being outcomes in shift-workers. Much of the existing literature relies on subjective sleep measures or laboratory-based protocols, both of which present limitations when applied to populations with irregular sleep-wake schedules. Laboratory studies commonly assume consolidated, monophasic sleep occurring at fixed times, making them less applicable to the fragmented and variable sleep patterns characteristic of shift-workers (Åkerstedt, 2003; Kantermann et al., 2012). Similarly, self-reported sleep measures may be particularly unreliable in shift-working populations due to fragmented sleep episodes, irregular schedules, and difficulties recalling sleep timing and duration accurately (Lauderdale et al., 2008). Evidence suggests that individuals commonly overestimate their sleep duration compared with objective actigraphy-based measurements (Cespedes et al., 2016), further highlighting the limitations of subjective sleep assessment. Together, these issues emphasise the need for objective, ecologically valid assessments of multidimensional sleep health in free-living shift-working populations.

Accordingly, the aim of this study was to determine the association between objectively measured composite sleep health and self-reported health and well-being outcomes in shift-workers. Specifically, this study examined associations with resilience, perceived stress, burnout, depressive symptoms, general health, and subjective sleeping troubles. Understanding these relationships may help inform more targeted approaches to improving sleep health in populations particularly vulnerable to chronic sleep disruption.

# Methods

## Participants

This study employed a cross-sectional observational design as a secondary analysis of previously collected data. A total of 152 participants were recruited from a national airline in the Southern Hemisphere through an internal email invitation. Eligible employees worked within one of five work units: Aircraft Maintenance and Engineering, Corporate, Customer Contact Centre, Short-Haul Cabin Crew, and Check-In and Baggage Crew. For the purposes of this study, shift-workers were defined as participants who recorded at least one work shift commencing before 06:00 or ending after 18:00 during the monitoring period. Recruitment was authorised by the Group Manager and conducted via internal email circulation.

Using the PASS 15 software and a linear regression model, we estimated that 82 participants would allow detection of a slope of 0.3 (or larger), assuming an independent variable standard deviation of 25 and a residual standard deviation of 23.85 (calculated assuming a correlation of r = .30 between the independent and dependent variables). This achieved 80.1% power to detect a change in slope from 0.00 with a type I error rate of 0.05. The planning effect was based on Cohen's conventional interpretation of r = .30 as a medium effect (Cohen, 1988). Prior studies have identified graded associations between composite sleep health and mental-health outcomes, including depressive symptoms and perceived stress (Dong et al., 2019; Furihata et al., 2020; Lee & Lawson, 2021), supporting the choice of a medium planning effect.

Ethics approval was obtained from the Auckland University of Technology Ethics Committee (#18/293). Written informed consent was obtained from all participants, including permission for de-identified data to be used for future research.

## Measures

Data were collected in free-living conditions over seven consecutive days. Three primary methods of data collection were used: daily log diaries, accelerometery, and web-based surveys.

### Daily log diaries

Participants completed daily log diaries recording the start and end times of sleep, naps, commutes, work, and exercise, as well as accelerometer wear time.

### Accelerometery

The Axivity AX3 was used to track 24-hour movement and sleep patterns. These devices have been validated against the ActiGraph GT3X+ (Rowlands et al., 2017) and have demonstrated reliability for sleep tracking (Doherty et al., 2017). Participants were instructed to wear the device continuously, including during water-based activities, for seven consecutive days. Data were downloaded using OMGUI (Open Movement, Newcastle University, Newcastle upon Tyne, UK) and batch processed using the GGIR R package (Migueles et al., 2019a). Sleep metrics, including sleep onset timestamp, total sleep time, sleep efficiency, and wake time, were calculated using the van Hees algorithm implemented within GGIR (van Hees et al., 2015). The algorithm incorporated participant sleep log information collected from the daily diaries. The specific GGIR configuration parameters used in this study are provided in the supplementary configuration file in Appendix Table 1.

For the purposes of this study, sleep metrics were selected based on both availability within the dataset and relevance to shift-working populations. Metrics derived from the van Hees algorithm included:

- Duration: mean total sleep time across all recorded sleep periods.
- Variability: coefficient of variation of total sleep time.
- Timing: mean sleep midpoint.
- Regularity: standard deviation of sleep midpoint.
- Efficiency: mean sleep efficiency across recorded sleep periods.

Composite sleep health scores were calculated by summing scores across all five sleep metrics, as described in Chapter 4. Briefly, each dimension was scored as 2 (optimal), 1 (sub-optimal/moderate), or 0 (poor) according to predefined threshold values. Where possible, thresholds were derived from published literature and public health guidelines. For metrics without established public health thresholds, values were determined through expert discussion and iterative synthesis. Scores across each dimension were summed to produce a final composite sleep health score ranging from 0 to 10.

Web-based survey

The web-based survey was delivered through the Qualtrics platform and completed using an iPad. The survey captured job characteristics, job demands, resilience, health and well-being, health behaviours, and demographic information.

Resilience was assessed using the 6-item Brief Resilience Scale (BRS), which measures an individual's ability to recover from stress. Each item is rated on a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), with higher scores indicating greater resilience. Other health and well-being outcomes were assessed using selected subscales from the Copenhagen Psychosocial Questionnaire II (COPSOQ II), including general health (1 item), sleeping troubles (4 items), burnout (4 items), perceived stress (4 items), depressive symptoms (4 items), somatic stress (4 items), and cognitive stress (4 items). General health was scored on a 5-point Likert scale ranging from 1 to 5. All other COPSOQ II subscales used response categories scored as 0, 25, 50, 75, or 100, with lower scores indicating better health outcomes. For both the BRS and COPSOQ II subscales, scores were calculated by averaging available item responses, with a minimum completion threshold of 50% required to derive a final score.

## Statistical Analysis

Participants were included in the analysis if they recorded at least one work shift starting before 06:00 or ending after 18:00 during the monitoring period and provided at least

four nights of sleep data. Descriptive statistics were used to summarise participant characteristics and the distribution of study variables.

Linear regression analyses were conducted to examine associations between composite sleep health and health and well-being outcomes. The independent variable was the composite sleep health score (range 0–10), while dependent variables included resilience, general health, sleeping troubles, burnout, depressive symptoms, and somatic, cognitive, and perceived stress. Each outcome variable was modelled separately. Model residuals were visually inspected to assess regression assumptions, and $R^2$ values were obtained as indicators of model fit.

A sensitivity analysis was conducted by repeating the regression analyses using a relaxed inclusion criterion of more than one night of recorded sleep data to examine the influence of the monitoring-duration criterion on the observed associations.

## Results

A total of 89 participants met the inclusion criteria for this study (shift-worker, ≥ 4 nights of recorded sleep data), with 88 participants completing the survey measures. The sample was predominantly female (62.9%) and of European ethnicity (66.3%), with participants distributed relatively evenly across age groups. Detailed demographic characteristics are presented in Table 5-1.

*Table 5-1.*

*Demographic characteristics of the sample*

| Variable | Category | n | % |
|---|---|---|---|
| Ethnicity* | Māori | 6 | 6.7% |
| | Pacific | 16 | 18.0% |
| | Asian | 15 | 16.9% |
| | MELAA | 4 | 4.5% |
| | European | 59 | 66.3% |
| Relationship Status | Single and never married | 21 | 23.6% |
| | Married or living with a partner | 56 | 62.9% |
| | Permanently separated or divorced | 10 | 11.2% |
| | Missing | 2 | 2.2% |
| Do you have children? | Yes | 49 | 55.1% |
| | No | 37 | 41.6% |
| | Missing | 3 | 3.3% |
| Gender | Male | 31 | 34.8% |
| | Female | 56 | 62.9% |
| | Missing | 2 | 2.2% |
| Age (years) | <30 | 20 | 22.5% |
| | 30-39 | 23 | 25.8% |
| | 40-49 | 21 | 23.6% |
| | 50-59 | 14 | 15.7% |
| | 60+ | 10 | 11.2% |
| | Missing | 1 | 1.1% |

*Participants were able to select multiple ethnicities

Table 5-2 presents descriptive statistics for composite sleep health and health and well-being outcomes. The mean composite sleep health score was 2.93 ± 2.06. Mean scores for resilience, general health, sleeping troubles, burnout, perceived stress, depressive symptoms, somatic stress, and cognitive stress are also presented in Table 5-2.

*Table 5-2.*

*Descriptive statistics for composite sleep health and well-being measures (n = 88)*

| Variable | Mean | SD |
|---|---|---|
| Composite sleep health score | 2.93 | 2.06 |
| General health | 2.83 | 1.05 |
| Brief Resilience Scale | 21.3 | 5.07 |
| Sleeping Troubles score | 49.1 | 23.5 |
| Burnout score | 55.5 | 22.7 |
| Perceived Stress score | 41.8 | 23.1 |
| Depressive Symptoms score | 24.5 | 19.7 |
| Somatic Stress score | 24.4 | 17.9 |
| Cognitive Stress score | 28.2 | 18.1 |

Linear regression analyses were conducted to examine associations between composite sleep health and psychological and health-related outcomes (Table 5-3). Composite sleep health was not significantly associated with resilience, general health, burnout, perceived stress, depressive symptoms, somatic stress, or cognitive stress. The association with subjective sleeping troubles approached statistical significance (B =-2.064, SE = 1.202, 95% CI:-4.454 to 0.326, p = 0.09), although explanatory power remained low ($R^2 = 0.033$).

*Table 5-3.*

*Linear regression results (n = 88)*

| Variable | Coefficient (β) | SE | Lower CI | Upper CI | p | $R^2$ |
|---|---|---|---|---|---|---|
| Brief Resilience Scale | -0.083 | 0.264 | -0.607 | 0.441 | 0.754 | 0.001 |
| General Health perception | -0.029 | 0.055 | -0.138 | 0.080 | 0.596 | 0.003 |
| Sleeping Troubles (subjective) | -2.064 | 1.202 | -4.454 | 0.326 | 0.090 | 0.033 |
| Burnout | 0.410 | 1.180 | -1.937 | 2.756 | 0.729 | 0.001 |
| Perceived Stress | 0.476 | 1.205 | -1.919 | 2.871 | 0.694 | 0.002 |
| Depressive symptoms | 0.195 | 1.024 | -1.841 | 2.230 | 0.850 | <0.001 |
| Somatic Stress | 0.288 | 0.933 | -1.566 | 2.142 | 0.758 | 0.001 |
| Cognitive Stress | 0.998 | 0.937 | -0.864 | 2.864 | 0.290 | 0.013 |

A sensitivity analysis was conducted to examine the effect of the monitoring-duration inclusion criterion (≥4 nights of measured sleep). The analyses were repeated using a relaxed inclusion criterion of >1 night of recorded sleep (see Appendix Table 4). Relaxing the inclusion criterion did not meaningfully alter the findings or improve model explanatory power. Composite sleep health remained a poor predictor of resilience, stress, burnout, depressive symptoms, and other psychosocial outcomes.

# Discussion

## Summary of key findings

The aim of this study was to examine the association between objectively measured composite sleep health and self-reported psychosocial and health-related outcomes in shift-workers. Overall, objectively measured composite sleep health demonstrated limited explanatory value for resilience, general health, burnout, perceived stress, depressive symptoms, somatic stress, and cognitive stress. Although the association with subjective sleeping troubles approached statistical significance, the explanatory power of the model remained low. Collectively, these findings suggest that objectively measured composite sleep health may not map directly onto perceived psychosocial well-being in shift-workers.

## Comparison with prior literature and potential explanations

The present findings differ from several previous studies reporting associations between composite sleep health and psychological outcomes. For example, Furihata et al. (2020) found that poorer composite sleep health was associated with greater depressive symptoms among Japanese female nurses, while Dong et al. (2019) reported associations between sleep health and emotional, cognitive, and social functioning in adolescents with an eveningness chronotype. Similarly, Lee and Lawson (2021) found that multidimensional sleep health was associated with improved psychological outcomes. In contrast, the current study did not identify significant associations between objectively measured composite sleep health and psychosocial outcomes among shift-workers.

One potential explanation for these differing findings relates to the distinction between objective and subjective sleep constructs. Many prior studies relied partly or entirely on self-reported sleep measures, often incorporating dimensions such as sleep satisfaction or perceived sleep quality. In contrast, the present study derived composite sleep health exclusively from objective accelerometer-based measures, including sleep duration, variability, timing, regularity, and efficiency. While objective measures quantify

behavioural and physiological characteristics of sleep, subjective measures also capture an individual's perception and interpretation of their sleep experience. Psychological outcomes such as stress, burnout, depressive symptoms, and resilience may align more closely with perceived sleep quality than with objective sleep behaviour alone.

This distinction may be particularly relevant in shift-working populations, where sleep is frequently fragmented, irregular, and distributed across varying times of day. Individuals experiencing similar objective sleep patterns may perceive and respond to those sleep patterns differently depending on coping capacity, occupational demands, stress appraisal, and personal expectations surrounding sleep. Consequently, objective multidimensional sleep health and subjective psychosocial well-being may represent related, but distinct, components of the broader sleep–health relationship.

Differences in psychological outcome measures may also contribute to the divergence between the present findings and previous research. Prior studies commonly utilised symptom-specific clinical measures, such as the CES-D, PHQ-9, GAD-7, or structured diagnostic interviews. In contrast, the current study focused on broader constructs of psychosocial functioning and well-being using the COPSOQ II and Brief Resilience Scale. It is therefore possible that objective composite sleep health relates differently to broad perceptions of well-being than to more targeted clinical symptom measures.

Methodological differences in sleep measurement may also have contributed to variation across studies. Previous research has demonstrated substantial disagreement between subjective and objective sleep measures, particularly among individuals with irregular sleep schedules or disrupted sleep patterns. Self-reported sleep measures often allow participants to reflect on their general perceptions of sleep over extended periods, whereas objective measures are restricted to recorded monitoring periods and may not fully capture the lived experience of chronic sleep disruption. Although a minimum of four nights of recorded sleep was required in the present study, sensitivity analyses using more relaxed inclusion criteria did not meaningfully alter the findings, suggesting that measurement duration alone was unlikely to explain the observed null associations.

## Strengths and limitations

This study has several strengths. First, it utilised objective accelerometer-derived measures of multidimensional sleep health, reducing reliance on self-reported sleep assessment and improving ecological validity in a free-living shift-working population. Second, the study extended existing composite sleep health research beyond healthcare-based samples by including workers from a range of occupational settings within the aviation industry. Finally, the use of validated psychosocial outcome measures and predefined composite sleep health thresholds strengthened the methodological rigour of the study.

Several limitations should also be acknowledged. The sample was recruited from a single organisation, potentially limiting generalisability to other occupational settings and shift-working populations. Although objective sleep measurement reduces self-report bias, the exclusion of subjective sleep satisfaction and perceived sleep quality may have reduced sensitivity to psychosocial outcomes. The monitoring period may also not have fully captured long-term habitual sleep patterns, although sensitivity analyses suggested that relaxing inclusion thresholds did not substantially alter the findings. Finally, the cross-sectional design limits causal interpretation of the observed associations.

## Implications for future research

The present findings suggest that objectively measured composite sleep health alone may have limited utility for explaining self-reported psychosocial well-being in shift-workers. Rather than contradicting existing sleep-health theory, these findings may indicate that objective and subjective sleep measures capture different aspects of the sleep–health relationship. Future research should therefore investigate whether hybrid models incorporating both objective sleep characteristics and subjective sleep perceptions provide stronger explanatory value for psychological well-being outcomes.

The findings also support the need for broader multidimensional approaches to health assessment in shift-working populations. Psychosocial well-being is likely influenced by

numerous interacting behavioural, occupational, and lifestyle factors beyond sleep alone. Future studies should therefore examine how composite sleep health interacts with other behavioural determinants, including physical activity, sedentary behaviour, and broader 24-hour time-use composition. Given the irregular schedules inherent to shift-work, integrated 24-hour behavioural frameworks may provide a more comprehensive understanding of how sleep and daily behaviours collectively influence well-being outcomes.

## Conclusion

This study provides a novel examination of objectively measured composite sleep health and psychosocial well-being outcomes in shift-workers. Contrary to several previous studies using subjective or mixed-method sleep measures, objectively measured composite sleep health demonstrated limited explanatory value for resilience, stress, burnout, depressive symptoms, and related well-being outcomes. These findings suggest that objective and subjective sleep constructs may capture different dimensions of the sleep–health relationship. Future research should continue to explore multidimensional and integrated approaches to understanding sleep, behaviour, and well-being in shift-working populations.

# Chapter 6 – The Association Between Composite Sleep Health and Health Behaviours in Shift-Workers

## Prelude

The preceding chapter examined whether objectively measured composite sleep health (CSH) was associated with self-reported psychosocial and health-related outcomes in shift-workers. Although the cohort demonstrated generally low CSH, few meaningful associations were observed with resilience, stress, burnout, depressive symptoms, or perceived general health. The strongest relationship was with subjective sleeping troubles, though this explained only a small proportion of variance. Together, these findings suggested that objectively measured CSH may capture different aspects of sleep-related functioning than subjective psychosocial measures in shift-working populations.

Building on these findings, the current chapter examines whether objectively measured CSH is associated with common health-related behaviours that may influence, or be influenced by, sleep. Specifically, this chapter investigates behaviours including physical activity, caffeine use, alcohol intake, smoking, diet, and sleep aid use among shift-workers. In doing so, the focus shifts from broad psychosocial outcomes to modifiable behavioural factors that may have more direct relationships with multidimensional sleep health in free-living conditions. This chapter also provides a conceptual bridge to the subsequent chapter, which explores sleep health within the broader context of 24-hour time-use behaviours in shift-workers.

## Abstract

Introduction: Sleep health is increasingly recognised as a multidimensional construct encompassing both sleep quantity and quality. Shift-workers are particularly vulnerable to disrupted sleep due to irregular work schedules and circadian misalignment. Although several lifestyle behaviours are commonly linked to sleep, less is known about how these behaviours relate to objectively measured composite sleep health in shift-working populations. This study examined whether health-related behaviours explain variance in composite sleep health among shift-workers.

Methods: This cross-sectional study analysed data from shift-working employees recruited from a major airline in the South Pacific. Participants were included if they recorded at least one work shift beginning before 06:00 or ending after 18:00 and provided at least three nights of valid accelerometer-derived sleep data. Sleep was measured using Axivity AX3 accelerometers worn continuously over seven consecutive days, supplemented by daily sleep and work diaries. Composite sleep health was calculated from five objectively measured dimensions: duration, regularity, variability, efficiency, and timing. Each dimension was scored from 0 to 2 and summed to produce a total score ranging from 0 to 10. Health behaviours were assessed using a web-based survey and included fruit and vegetable intake, sugary drink consumption, alcohol use, smoking, caffeine use, sleep aid use, resistance training, and self-reported physical activity. Linear regression models were used to examine associations between each behaviour and composite sleep health. Variables with $p \leq .25$ in unadjusted analyses were entered into adjusted models controlling for age, gender, and BMI.

Results: A total of 88 shift-workers were included. Composite sleep health was generally low, with most participants scoring in the lower half of the composite sleep health scale and no participants scoring between 9 and 10. In unadjusted analyses, caffeine use was significantly associated with higher composite sleep health scores. After adjustment for age, gender, and BMI, caffeine use remained the only significant behavioural predictor of composite sleep health. Other health behaviours, including diet, alcohol use, smoking, sleep aid use, and physical activity, were not significantly associated with composite sleep

health. Overall, the regression models explained relatively small proportions of variance in composite sleep health.

Conclusions: Most self-reported health behaviours explained little variance in objectively measured composite sleep health among shift-workers. Caffeine use was associated with higher composite sleep health scores, although interpretation is limited by the cross-sectional design and lack of data regarding caffeine timing and dosage. Future research should consider the timing and context of behaviours across the 24-hour day when examining sleep health in shift-working populations.

# Introduction

Sleep health is increasingly recognised as a multidimensional construct encompassing dimensions such as duration, efficiency, timing, and regularity (Buysse, 2014). These dimensions can be integrated into a composite sleep health (CSH) score, providing a more holistic evaluation of sleep than single indicators such as total sleep time alone (Ohayon et al., 2017). By combining multiple dimensions, CSH captures patterns and interactions within sleep behaviour that isolated measures may overlook. The use of objective monitoring methods such as accelerometery further strengthens sleep assessment by providing detailed measures of sleep behaviour in free-living conditions (van Hees et al., 2015).

Shift-workers represent a population particularly vulnerable to disrupted sleep health. Irregular work schedules that conflict with circadian rhythms are consistently associated with shorter sleep duration, lower sleep efficiency, and greater variability in sleep timing (Crowther et al., 2022; Kecklund & Axelsson, 2016; Vetter, 2020). These disruptions contribute to elevated risks of cardiovascular disease, metabolic dysfunction, and poorer mental health outcomes (Boivin et al., 2022; Gan et al., 2015; Vyas et al., 2012). Although the adverse effects of shift-work on sleep are well established, relatively few studies have explored which modifiable health behaviours may contribute to variation in sleep health among shift-workers. Moving beyond broad sleep hygiene recommendations, examining these behavioural relationships may help identify more targeted strategies to support sleep in this high-risk population.

Modifiable lifestyle behaviours, including physical activity, diet quality, caffeine and alcohol consumption, smoking, and the use of sleep aids, are commonly emphasised in public health approaches to improving sleep (Irish et al., 2015). Evidence consistently supports beneficial effects of regular physical activity on sleep, although these effects appear to vary according to the type, timing, intensity, and context of activity (Alnawwar et al., 2023; Kubala et al., 2020; Skarpsno et al., 2018). By contrast, caffeine and alcohol are well documented to disrupt sleep architecture, though their effects are influenced by timing, dosage, and the behavioural demands associated with shift-work (Drake et al.,

2013; Gardiner et al., 2024). Importantly, much of the existing evidence has been derived from general populations or from studies relying on subjective sleep measures. Consequently, less is known about how these behaviours relate to objectively measured CSH in shift-working populations.

Methodological limitations further constrain current understanding. Previous research has often examined lifestyle behaviours in isolation or relied on limited sleep indicators such as sleep duration or self-rated sleep quality (Buysse, 2014). Reliance on self-report measures for both sleep and health behaviours also increases the potential for recall and reporting bias (Lauderdale et al., 2008). There is therefore a need for studies that consider multiple lifestyle behaviours simultaneously and examine their relationships with comprehensive, objectively derived measures of sleep health.

Given these gaps, this study aimed to examine how well a range of health-related behaviours, including physical activity, fruit and vegetable intake, sugary drink consumption, alcohol use, smoking, caffeine use, and sleep aid use, explain variance in composite sleep health among shift-workers. By focusing on a shift-working population and using accelerometer-derived sleep metrics, this study provides a more ecologically valid and behaviourally grounded perspective on factors associated with sleep health in this at-risk group.

# Methods

## Participants

This study is a cross-sectional analysis of data originally collected to examine physical activity in the workplace. The current study repurposes these data to investigate the associations between composite sleep health and health-related behaviours among shift-workers.

A total of 152 participants were recruited in 2018 from a major airline in the South Pacific, spanning five workplace units: Aircraft Maintenance and Engineering, Corporate,

Customer Contact Centre, Short-Haul Cabin Crew, and Check-In and Baggage Crew. Recruitment was conducted through internal email invitations approved by the Group Manager.

Eligibility for the current analysis required participants to have recorded at least one work shift that began before 06:00 or ended after 18:00 and to have at least three nights of valid sleep data recorded by the AX3 accelerometers. Ethical approval was obtained from the Auckland University of Technology Ethics Committee (#18/293), and all participants provided informed consent for the de-identified data to be used in future research.

## Measures

Data were collected in free-living conditions over seven consecutive days using three primary tools: daily log diaries, accelerometers, and a web-based survey. Additional biometric data, including height, weight, and blood pressure, were measured by a trained researcher.

### Daily log Diaries

Participants completed daily log diaries recording the start and end times of sleep, naps, commutes, work, and exercise, as well as accelerometer wear time. These diaries were used to contextualise objective activity and sleep data and to supplement accelerometer processing algorithms. Because this study specifically evaluated shift-workers, self-reported work hours were also used to classify participants. Individuals who recorded at least one work shift beginning before 06:00 or ending after 18:00 were categorised as shift-workers.

### Accelerometery

Participants wore Axivity AX3 accelerometers continuously for seven consecutive days on the mid-thigh (and low-back), including during water-based activities. Data were downloaded using OmGui (Open Movement, Newcastle University, Newcastle upon Tyne, UK) and batch processed using the GGIR R package (Migueles et al., 2019a). Sleep

parameters were estimated using the van Hees algorithm (van Hees et al., 2015), incorporating accelerometer signals and corresponding diary information. The specific GGIR configuration parameters used in this study are provided in the supplementary configuration file in Appendix Table 1.

The following sleep metrics were extracted: mean total sleep time (TST) per night (Duration), coefficient of variation of TST (Variability), mean sleep efficiency (Efficiency), mean midpoint of sleep (Timing), and standard deviation of sleep midpoint (Regularity).

Composite sleep health (CSH) scores were derived from these objective sleep metrics using the scoring framework established in Chapter 4. Briefly, each sleep dimension was classified using thresholds derived from published literature or expert-informed criteria where established thresholds were unavailable. Dimensions were scored on a 0–2 scale representing poor, moderate, or optimal sleep health, respectively, and summed to produce a total CSH score ranging from 0–10.

Web-based survey

Survey data were collected using Qualtrics administered on iPads. The survey captured demographic characteristics including age, gender, and BMI, as well as workplace demands, validated health outcome measures, and health-related behaviours.

Nutritional behaviours included fruit and vegetable intake, which were each assessed as the number of servings usually consumed per day. Response categories ranged from “I don’t eat [fruit/vegetables]” to “4 or more servings per day” and were treated as ordinal variables. Sugary drink consumption was assessed by asking participants how often they consumed one or more sugary drinks, with response categories ranging from “never” to “7 or more times per week” (ordinal).

Alcohol use was assessed using three questions. Participants reported the frequency of alcohol consumption using categories ranging from “I do not drink alcohol” to “4 or more times per week” (ordinal). They also reported the typical number of drinks consumed per drinking occasion, with response categories ranging from “1–2 drinks” to “12 or more drinks” (ordinal). Frequency of heavy drinking occasions, defined as consuming six or

more drinks on one occasion, was assessed using response categories ranging from "never" to "daily or almost daily" (ordinal).

Shift management aids: Participants were also asked, "Do you regularly use one or more of the following to cope with your shift work?" Response options for caffeine, alcohol, prescription sleep medications (e.g., melatonin, zopiclone, temazepam, triazolam), over-the-counter sleep aids (e.g., Panadol Night, Unisom), and herbal/supplement-based remedies (e.g., magnesium, sleep drops) were recorded dichotomously (Yes/No) and treated as nominal variables.

Physical activity was assessed using self-reported moderate physical activity (MPA), vigorous physical activity (VPA), and resistance training participation. Participants reported MPA and VPA according to days per week (0–7; ordinal), average hours per day (0–24; scale), and average minutes per day (0–60; scale). Resistance training was recorded as the number of sessions completed per week (scale). A derived total physical activity variable was calculated as continuous MET-hours per week.

Current smoking status was reported dichotomously as Yes/No (nominal).

## Statistical Analysis

Linear regression analyses were conducted to examine associations between composite sleep health (CSH) scores and individual health behaviours. Initial models were unadjusted. Independent variables demonstrating associations at $p \leq .25$ in unadjusted analyses were subsequently entered into adjusted models controlling for age, gender, and BMI, consistent with purposeful variable selection approaches recommended for multivariable modelling (Hosmer et al., 2013; Kecklund & Axelsson, 2016; Knutson, 2010). Participants with missing data for a given health behaviour variable (e.g., caffeine use) were excluded from the corresponding regression model using complete case analysis.

An a priori power analysis was conducted using PASS (version 15) to estimate the required sample size for the adjusted regression models. Each model included three covariates

(age, gender, BMI) with one health behaviour entered as the predictor of interest. A medium effect size was assumed ($f^2 = 0.15$, equivalent to $R^2 \approx 0.13$), with $\alpha$ set at 0.05 and desired power of 0.85. Results indicated that a minimum of 68 participants were required. The final analytic sample (n = 88) exceeded this threshold, providing adequate power to detect effects of at least medium magnitude.

# Results

A total of 88 shift-working employees met the inclusion criteria for this study (shift-worker, recorded ≥ 3 nights of sleep data, completed study-related sections of the survey). The sample was reasonably equally distributed across both age category and BMI range. Table 6-1 provides a detailed demographic breakdown of the sample.

*Table 6-1.*

*Demographic characteristics*

| Variable | Category | n | % |
|---|---|---|---|
| Gender | Male | 31 | 35.2% |
| | Female | 56 | 63.6% |
| | Missing | 1 | 1.1% |
| Age (years) | <30 | 20 | 22.7% |
| | 30-39 | 23 | 26.1% |
| | 40-49 | 21 | 23.8% |
| | 50-59 | 14 | 15.9% |
| | 60+ | 10 | 11.3% |
| | Missing | 0 | 0% |
| BMI Range | Ideal, < 25 | 28 | 31.8% |
| | High, 25-29.99 | 31 | 35.2% |
| | Very High, 30 or more | 27 | 30.7% |
| | Missing | 2 | 2.3% |
| Composite Sleep Health Score | 0-2 | 47 | 53.4% |
| | 3-5 | 35 | 39.8% |
| | 6-8 | 6 | 6.8% |
| | 9-10 | 0 | 0% |

Table 6-2 shows statistical details of all unadjusted health behaviour models. In the unadjusted linear regression analyses, most health behaviours did not show a statistically significant relationship with composite sleep health (CSH). The only statistically significant association observed was for caffeine use ($p = .042$), where participants reporting caffeine use to cope with shift work demonstrated higher composite sleep health scores. Several

additional variables demonstrated borderline associations with CSH, including alcohol consumption frequency per week (p = .096), sugary drink frequency (p = .152), smoking status (p = .161), derived moderate physical activity (MPA) minutes per week (p = .167), and total MET hours per week (p = .210).

*Table 6-2.*

*Unadjusted linear regression models*

| Parameter | n | β | SE | Lower CL | Upper CL | p | $R^2$ |
|---|---|---|---|---|---|---|---|
| Fruit & Veg Combined | 86 | -.042 | .106 | -.251 | .168 | .695 | .002 |
| Sugary drinks | 86 | -.199 | .138 | -.473 | .075 | .152 | .021 |
| Alcohol (Frequency/week) | 86 | .313 | .186 | -.057 | .682 | .096 | .028 |
| Alcohol (drinks/day when drinking) | 63 | -.328 | .315 | -.957 | .301 | .302 | .015 |
| Alcohol (6 or more in 1 occasion frequency) | 63 | -.137 | .316 | -.767 | .492 | .665 | .003 |
| Smoking (Y/N) | 86 | 1.013 | .717 | -.410 | 2.437 | .161 | .020 |
| Caffeine (Y/N) | 51 | 2.000 | .961 | .076 | 3.924 | .042 | .069 |
| Sleep Aid Combined (Y/N) | 51 | .422 | .370 | -.318 | 1.162 | .258 | .022 |
| Derived MPA min/week | 87 | -.006 | .004 | -.015 | .003 | .167 | .019 |
| Derived VPA min/week | 87 | -.004 | .005 | -.014 | .007 | .468 | .005 |
| Resistance training days/week | 77 | .004 | .129 | -.253 | .260 | .978 | .000 |
| Total MET hrs/week | 87 | -.011 | .009 | -.028 | .006 | .210 | .016 |

β = unstandardised coefficient; SE = standard error; CL = confidence limit; MPA = moderate physical activity; VPA = vigorous physical activity

From the unadjusted models, any health behaviour with a $p \leq 0.25$ was subsequently entered into a model adjusted for gender, age, and BMI (Kecklund & Axelsson, 2016; Knutson, 2010). Table 6-3 reports the statistical outcomes for adjusted models including sugary drink frequency, alcohol consumption frequency per week, smoking status, caffeine use, derived self-reported MPA minutes per week, and total MET hours per week.

Among the adjusted models, caffeine use remained the only statistically significant behavioural predictor of CSH (p = .023). The caffeine use model demonstrated the largest explained variance of the adjusted models presented ($R^2$ = .164), with caffeine use

associated with a 2.294-point higher composite sleep health score. However, this model also had the smallest analytic sample (n = 50).

Alcohol consumption frequency per week approached statistical significance in the adjusted model (p = .093), while sugary drink frequency, smoking status, derived MPA minutes per week, and total MET hours per week did not demonstrate significant associations with CSH after adjustment. Although BMI emerged as a statistically significant covariate in both the derived MPA minutes per week model (p = .028) and total MET hours per week model (p = .021), age and gender were generally not significant across models. An exception was observed in the alcohol frequency model, where gender reached statistical significance (p = .045). Overall, the adjusted models explained between 9.2% and 16.4% of variance in composite sleep health scores.

*Table 6-3.*

*Adjusted models for Gender, Age, and BMI*

| Model / Predictor | n | β | SE | LL | UL | p | $R^2$ |
|---|---|---|---|---|---|---|---|
| Adjusted Model 1: Sugary drink frequency | 85 | | | | | | |
| Gender | | .713 | .462 | -.205 | 1.632 | .126 | |
| Age | | -.004 | .016 | -.035 | .028 | .819 | .092 |
| BMI | | -.072 | .037 | -.146 | .002 | .055 | |
| Sugary drink frequency | | -.106 | .146 | -.395 | .183 | .468 | |
| Adjusted Model 2: Alcohol frequency/week | 85 | | | | | | |
| Gender | | .933 | .460 | .019 | 1.847 | .045* | |
| Age | | -.005 | .015 | -.036 | .025 | .735 | .115 |
| BMI | | -.061 | .037 | -.135 | .013 | .104 | |
| Alcohol frequency/week | | .331 | .195 | -.056 | .718 | .093 | |
| Adjusted Model 3: Smoking (Y/N) | 85 | | | | | | |
| Gender | | .854 | .456 | -.051 | 1.760 | .064 | |
| Age | | -.003 | .015 | -.034 | .027 | .843 | .107 |
| BMI | | -.070 | .037 | -.142 | .003 | .060 | |
| Smoking (Y/N) | | 1.020 | .719 | -.408 | 2.447 | .159 | |
| Adjusted Model 4: Caffeine use (Y/N) | 50 | | | | | | |
| Gender | | .872 | .644 | -.420 | 2.164 | .181 | |
| Age | | .023 | .022 | -.021 | .068 | .302 | .164 |
| BMI | | -.093 | .073 | -.239 | .053 | .206 | |
| Caffeine use | | 2.294 | .981 | .326 | 4.262 | .023* | |
| Adjusted Model 5: Derived MPA min/week | 85 | | | | | | |
| Gender | | .714 | .455 | -.189 | 1.618 | .120 | |
| Age | | -.001 | .015 | -.031 | .029 | .946 | .104 |
| BMI | | -.081 | .036 | -.153 | -.009 | .028* | |
| Derived MPA min/week | | -.006 | .005 | -.015 | .003 | .193 | |
| Adjusted Model 6: Total MET hrs/week | 85 | | | | | | |
| Gender | | .759 | .457 | -.149 | 1.667 | .100 | |
| Age | | .002 | .015 | -.029 | .033 | .905 | .109 |
| BMI | | -.085 | .036 | -.156 | -.013 | .021* | |
| Total MET hrs/week | | -.009 | .009 | -.027 | .009 | .318 | |

β = unstandardised coefficient; SE = standard error; CI = confidence interval; LL = lower limit; UL = upper limit; MPA = moderate physical activity. *p < .05.

# Discussion

This study examined associations between objectively measured composite sleep health (CSH) and self-reported health behaviours among shift-workers. Overall, few health behaviours demonstrated meaningful associations with CSH. In unadjusted analyses, caffeine use was the only behaviour significantly associated with higher CSH scores. After adjustment for age, gender, and BMI, caffeine use remained the only significant behavioural predictor of CSH. Other behaviours, including diet, alcohol use, smoking, sleep aid use, and physical activity, were not significantly associated with CSH. Although several variables approached significance in unadjusted or adjusted models, the overall variance explained by the models remained modest.

## Caffeine use

Caffeine use was positively associated with CSH in adjusted models, a finding that initially appears inconsistent with literature demonstrating that caffeine consumption close to bedtime impairs sleep quality and sleep onset (Drake et al., 2013). However, the relationship between caffeine and sleep in shift-working populations may be more context dependent than conventional sleep hygiene models suggest.

Caffeine is widely used by shift-workers as a fatigue-management strategy to maintain alertness and operational performance during irregular work schedules (Shriane et al., 2020). Experimental research demonstrates that caffeine can improve vigilance, cognitive performance, and perceived alertness during periods of sleep restriction or circadian disruption (Lieberman et al., 2002). Population-level evidence further suggests that shift-workers may not necessarily consume greater quantities of caffeine than day workers, but instead consume caffeine at different times of day to manage fatigue and maintain wakefulness (Lieberman et al., 2019). Strategic caffeine use, including approaches such as the “coffee nap”, has also been shown to temporarily improve alertness and performance (Hayashi et al., 2003).

The present findings may therefore reflect strategic or adaptive caffeine use among workers who are otherwise functioning relatively well within the constraints of shift-work.

It is also possible that caffeine use acted as a proxy marker for workers who were more proactive in managing fatigue. However, interpretation should remain cautious, as caffeine timing, dosage, and source were not assessed. Additionally, the adjusted caffeine model had the smallest analytic sample, limiting confidence in the stability and generalisability of the finding.

Physical activity

Contrary to expectations and prior literature, physical activity measures were not significantly associated with CSH in adjusted models. Although total MET hours per week and moderate physical activity demonstrated borderline associations in some unadjusted analyses, these relationships were attenuated following adjustment for demographic covariates.

Existing literature generally supports a beneficial relationship between physical activity and sleep health (Alnawwar et al., 2023; Kubala et al., 2020; Skarpsno et al., 2018). However, recent evidence suggests this relationship is highly dependent on the domain, timing, intensity, and context of activity. Occupational physical activity has been associated with poorer sleep outcomes and insomnia symptoms, whereas leisure-time physical activity is generally associated with improved sleep, reflecting the so-called "physical activity paradox" (Gupta et al., 2020; Hallman et al., 2017). Longitudinal evidence further suggests that high occupational physical activity may increase the risk of future sleep disturbances, particularly in some occupational groups (Wang et al., 2025). Exercise timing may also be important, with prolonged vigorous evening exercise shown to impair sleep onset and continuity (Alnawwar et al., 2023), while moderate-intensity exercise may help preserve sleep quality around night shifts (Wu et al., 2025).

In the present study, physical activity was assessed using broad self-reported weekly estimates without distinguishing between occupational and leisure activity or accounting for activity timing relative to sleep opportunities. These measurement limitations may partly explain the absence of clear associations between physical activity and objectively measured CSH in this shift-working cohort.

### Interpretation of non-significant results

Most dietary and substance-use behaviours were not significantly associated with CSH. Although some variables demonstrated moderate effect sizes or approached statistical significance, confidence intervals were generally wide and explained variance remained low across models. Collectively, these findings suggest that individual health behaviours may explain only a small proportion of variance in objectively measured multidimensional sleep health among shift-workers.

These findings also reinforce the possibility that CSH captures broader behavioural and physiological patterns not easily explained by isolated lifestyle factors alone. Sleep in shift-working populations is likely influenced by a complex interaction between circadian disruption, work scheduling, recovery opportunities, environmental constraints, and behavioural adaptation strategies.

## Strengths and limitations

A major strength of this study was the use of objectively measured sleep data derived from accelerometery, allowing more reliable assessment of sleep behaviour than subjective self-report alone (Neil-Sztramko et al., 2014). The multidimensional CSH framework also provided a broader representation of sleep health than single indicators such as sleep duration (Kecklund & Axelsson, 2016). Restricting the sample to verified shift-workers with adequate sleep data further enhanced ecological validity and relevance to this high-risk population.

Several limitations should also be acknowledged. The cross-sectional design precludes causal inference. Health behaviours were assessed via self-report and may therefore be subject to recall and social desirability bias (Neil-Sztramko et al., 2014). Important confounders such as chronotype, shift schedule characteristics, stress, and timing of behaviours were not measured (Krishnan & Collop, 2006). Sample sizes were also smaller for some adjusted models, particularly caffeine-related analyses, which may limit statistical stability and generalisability.

## Conclusion

This study examined associations between self-reported health behaviours and objectively measured composite sleep health among shift-workers. Overall, few behaviours demonstrated meaningful associations with CSH, with caffeine use emerging as the only significant behavioural predictor after adjustment for age, gender, and BMI. These findings suggest that multidimensional sleep health in shift-workers may not be strongly explained by isolated lifestyle behaviours alone.

The findings also highlight the importance of considering behavioural context when examining sleep in shift-working populations. Future research should move beyond aggregate behavioural measures to examine the timing, distribution, and context of daily activities in relation to sleep opportunities. Approaches such as compositional data analysis and isotemporal substitution may provide more nuanced insight into how the allocation of time across the 24-hour day influences sleep health in shift-workers.

# Chapter 7 – The Association Between Composite Sleep Health and 24-Hour Time-Use Behaviour in Shift-Workers

## Prelude

Chapter 6 examined whether common self-reported health behaviours were associated with objectively measured composite sleep health (CSH) in shift-workers. Overall, CSH was poor across the sample, with most participants scoring in the lower half of the CSH scale. Most self-reported health behaviours explained little variance in CSH, and after adjustment for age, sex, and BMI, caffeine use remained the only significant behavioural predictor. Interpretation of these findings was limited by the cross-sectional design, the reliance on self-reported behavioural measures, and the absence of information regarding the timing and context of behaviours across the day. Together, these findings suggested that examining behaviours as isolated variables may not adequately capture the broader behavioural environment in which sleep health occurs in shift-workers.

This chapter therefore shifts the focus from individual self-reported behaviours to the objective distribution of time across the full 24-hour day. Using compositional data analysis and isotemporal substitution modelling, the chapter examines how the relative balance between sleep, sedentary behaviour, light physical activity, and moderate-to-vigorous physical activity is associated with objectively measured CSH in shift-workers. By treating daily behaviours as interdependent components of a finite 24-hour period, this chapter extends the thesis into a broader movement-behaviour framework and provides the final empirical step towards understanding sleep health within the behavioural constraints of shift-work.

## Abstract

**Purpose**: Shift-workers experience disrupted sleep and constrained opportunities to distribute time across sleep, sedentary behaviour, light physical activity (LPA), and moderate-to-vigorous physical activity (MVPA). This study examined how objectively measured 24-hour time-use compositions relate to composite sleep health (CSH) in shift-workers using compositional data analysis and isotemporal substitution modelling.

**Methods**: Shift-workers from a major South Pacific airline completed seven days of continuous monitoring using thigh-worn accelerometers and paper diaries. Daily time use was summarised as a four-part 24-hour composition comprising sleep, sedentary behaviour, LPA, and MVPA. CSH was derived as a week-level score (0–10) from five accelerometer-derived sleep dimensions: duration, variability, efficiency, timing, and regularity. Associations between the movement composition and CSH were examined using isometric log-ratio-transformed compositional regression models adjusted for age, sex, BMI, and wear time. Compositional isotemporal substitution analysis estimated predicted differences in CSH associated with reallocations of time between behaviours.

**Results**: The analytic sample included 101 shift-workers (mean age 41.0 years; 63% women) contributing an average of 6.7 valid monitoring days. Mean CSH was 3.0/10, indicating generally poor sleep health across the cohort. The mean daily composition comprised approximately 864 minutes of sedentary behaviour, 82 minutes LPA, 81 minutes MVPA, and 414 minutes sleep. In adjusted compositional regression models, greater relative sedentary behaviour was associated with lower CSH ($\beta = -7.2$, $p < .001$), whereas greater relative sleep was associated with higher CSH ($\beta = 8.2$, $p < .001$). Associations for LPA and MVPA were not statistically significant. Isotemporal substitution analyses showed that reallocating 60 minutes away from sedentary behaviour and proportionally redistributing that time across the remaining behaviours was associated with a predicted increase in CSH ($\Delta = +1.06$; 95% CI 0.617 to 1.51). Conversely, reallocating 60 minutes away from sleep was associated with a predicted decrease in CSH ($\Delta = -1.51$; 95% CI −2.18 to −0.842).

Conclusions: In this cohort of shift-workers, composite sleep health appeared to be more strongly associated with the balance between sleep and sedentary behaviour than with LPA or MVPA. Reallocations that preserved or increased sleep while reducing sedentary behaviour showed the most favourable predicted associations with CSH. These findings support the importance of considering sleep health within a 24-hour movement-behaviour framework and highlight the potential relevance of sleep opportunity and sedentary exposure within shift-working populations.

# Introduction

Sleep is essential for health, with poor sleep linked to cardiometabolic disease, psychological distress, and poorer self-rated health outcomes (Furihata et al., 2017; Makarem et al., 2022; Paine et al., 2019). Increasingly, sleep is conceptualised as a multidimensional construct referred to as "sleep health," which incorporates dimensions such as duration, efficiency, timing, regularity, satisfaction, and alertness rather than relying on sleep duration alone (Buysse, 2014; Matricciani et al., 2024). Sleep health can be assessed using both subjective and objective methods, although accelerometery offers the advantage of capturing sleep within free-living conditions while simultaneously measuring waking movement behaviours that may influence sleep timing and architecture (van Hees et al., 2015; Zapalac et al., 2024).

Daily behaviours including sleep, sedentary behaviour, light physical activity (LPA), and moderate-to-vigorous physical activity (MVPA) are mutually dependent, meaning that increasing time in one behaviour necessarily reduces time in another (Dumuid et al., 2020; Matricciani et al., 2024). Time-use epidemiology therefore conceptualises health behaviours as components of a finite 24-hour composition, where behavioural trade-offs may influence physical and mental health outcomes (Curtis et al., 2023; Grgic et al., 2018). Compositional data analysis (CoDA) has emerged as an important methodological approach within this field because it accounts for the codependent nature of time-use data and enables estimation of how reallocating time between behaviours may relate to health outcomes (Dumuid et al., 2020; Pedišić, 2014). Previous studies have shown that daily activity compositions are associated with several dimensions of sleep health, including timing, efficiency, regularity, and subjective sleep quality (Curtis et al., 2023; Matricciani et al., 2024).

Although each day contains the same 1,440 minutes, opportunities to distribute time across behaviours are not experienced equally. For shift-workers, irregular schedules, night work, extended shifts, and rotating rosters can constrain opportunities for restorative sleep and alter when sedentary behaviour and physical activity occur (Lauren et al., 2020). These disruptions involve not only reduced sleep opportunity but also

altered timing and quality of behaviours across the 24-hour period. Consequently, shift-workers represent an important population for investigating how 24-hour activity compositions relate to sleep health.

Extensive evidence demonstrates that shift-work is associated with disrupted sleep and circadian misalignment (Warburton, 2006), while physical activity is often considered a protective health behaviour associated with improved sleep and cardiometabolic health (Warburton, 2006). However, relatively little research has examined these relationships through the lens of composite sleep health (CSH), particularly using fully objective measurement approaches in shift-working populations (Kubala et al., 2020). While previous studies have examined 24-hour activity compositions and sleep health in general populations (Curtis et al., 2023; Matricciani et al., 2024), limited work has focused specifically on shift-workers, where behavioural schedules are more constrained and sleep disruption is more pronounced. As a result, there remains a gap in understanding how objectively measured 24-hour time-use compositions relate to objectively measured CSH in shift-workers.

This study had two aims: (1) to examine how the relative distribution of objectively measured daily time-use behaviours is associated with objectively measured CSH in shift-workers; and (2) to estimate the predicted change in CSH associated with reallocating time between daily behaviours.

# Methods

## Participants

Participants were from a major South Pacific airline across five workplace units. This cross-sectional study measured each participant once. Inclusion in the analytic sample required at least one recorded work shift that began before 06:00 or ended after 18:00, and a minimum of three valid 24-hour days of accelerometery. Complete age, sex, and BMI data were also required. No additional exclusion criteria were applied. Ethical approval was obtained from the Auckland University of Technology Ethics Committee (#18/293). All

participants provided written informed consent, including permission for de-identified data use.

## Measures

### Daily log diaries

Paper diaries, later digitised, recorded start and end times for main sleep, naps, commutes, work, exercise, and accelerometer wear. Diary-reported bed and wake times were used to anchor detection of main sleep onset and offset during accelerometer processing.

### Accelerometery

Thigh-worn Axivity AX3 devices (Newcastle upon Tyne, UK) were affixed at the workplace to the dominant thigh with waterproof medical tape using a standardised protocol suitable for continuous wear, including water-based activities. Devices sampled at 100 Hz with a ±8 g range for a target monitoring period of 168 hours. Raw files were downloaded using OMGUI and processed in R using GGIR (version 3.3.0). As described in Chapter 3, sleep was estimated using the van Hees approach, anchored by diary-reported sleep times where available. When diary inputs were unavailable, sleep periods were estimated from accelerometer signals using GGIR default settings. Non-wear detection, auto-calibration, signal aggregation, and calendar day definitions followed GGIR defaults unless otherwise specified.

Daily time use was expressed as a four-part composition summing to 1,440 minutes per day: sleep, sedentary time, light physical activity (LPA), and moderate-to-vigorous physical activity (MVPA). Activity intensity thresholds were based on Euclidean Norm Minus One (ENMO) acceleration values in milli-gravitational units (mg), defined as sedentary (<40 mg), LPA (40–99 mg), moderate physical activity (100–399 mg), and vigorous physical activity (≥400 mg). MVPA was calculated as the combined duration of moderate and vigorous activity (≥100 mg). These were deemed the best thresholds available in GGIR for this wear location. Sleep duration was derived from GGIR-estimated sleep periods.

Analyses used the GGIR Part 5 person-summary outputs. A valid day required at least 16 hours of valid wear time. Participants were required to provide valid data for at least two-thirds of the monitoring period. Additionally, at least 90% of the sleep period time window was required to contain valid data. Full processing configuration details are provided in Appendix Table 5.

Composite sleep health

Composite sleep health (CSH) was derived from one week of accelerometer-assessed sleep data processed in GGIR and supported by sleep diary entries. As detailed in Chapter 4, CSH was operationalised as a multidimensional construct comprising five domains: sleep duration, variability, efficiency, timing, and regularity. Each domain was scored from 0 to 2 using predefined threshold criteria, with scores summed to produce a composite score ranging from 0 to 10, where higher scores reflected more favourable sleep health.

Briefly, duration was scored according to average nightly sleep duration; variability using the weekly coefficient of variation in total sleep time; timing according to average sleep midpoint; regularity using the standard deviation of mid-sleep timing across the week; and efficiency based on average sleep efficiency. Weekly summary values were calculated for each dimension prior to scoring, such that the final CSH score represented a week-level summary of habitual sleep health rather than nightly values. Full scoring procedures and threshold criteria are provided in Chapter 4.

## Statistical analysis

The primary exposure variable was a four-part 24-hour movement composition comprising sleep, sedentary behaviour, light physical activity (LPA), and moderate-to-vigorous physical activity (MVPA). Daily time spent in each behaviour was expressed in minutes and constrained to sum to 1,440 minutes per day. Behavioural durations were averaged across valid monitoring days to derive a participant-level weekly average composition for analysis. The movement composition was assessed for zero values prior

to compositional transformation. No zero values were present in the final analytic dataset; therefore, no zero-replacement procedure was required before log-ratio transformation.

Compositional data analysis (CoDA) was used to examine associations between the 24-hour movement composition and composite sleep health (CSH). Because compositional data are codependent and constrained within a finite total, movement behaviours were transformed into isometric log-ratio (ILR) coordinates using sequential binary partitions (SBPs). Separate SBP structures were specified so that each behaviour (sleep, sedentary behaviour, LPA, and MVPA) was represented as the first ILR coordinate (ILR1), reflecting that behaviour relative to the remaining three behaviours (Table 7-1). ILR coordinates were generated using the gsi.buildilrBase() function from the compositions package in R and entered into ordinary least squares linear regression models with participant-level CSH as the dependent variable.

*Table 7-1.*

*Sequential Binary Partition Structure Used to Generate ILR Coordinates*

| Model focus | ILR1 partition |
|---|---|
| Sedentary behaviour | Sedentary vs (LPA + MVPA + Sleep) |
| LPA | LPA vs (Sedentary + MVPA + Sleep) |
| MVPA | MVPA vs (Sedentary + LPA + Sleep) |
| Sleep | Sleep vs (Sedentary + LPA + MVPA) |

For each behaviour-specific composition, both unadjusted and adjusted regression models were examined. Adjusted models included total wear time, sex, BMI, and age as covariates. To address Aim 1, interpretation focused on the ILR1 coefficient because this represented the relative dominance of the behaviour of interest compared with the remaining parts of the composition. Statistical assumptions were assessed using residual and influence diagnostics.

Given that sleep contributed directly to the derivation of the CSH outcome, a sensitivity analysis was conducted to assess the robustness of findings and address potential conceptual overlap between the exposure and outcome variables. For this analysis, sleep was removed from the movement composition, resulting in a three-part waking behaviour composition comprising sedentary behaviour, light physical activity (LPA), and moderate-to-vigorous physical activity (MVPA). The three-part composition was transformed into isometric log-ratio (ILR) coordinates using the same compositional procedures described above and entered into equivalent unadjusted and adjusted regression models. Results from the sensitivity analysis were compared with those from the primary four-part models to determine whether observed associations were primarily driven by the inclusion of sleep within the composition.

To address Aim 2, compositional isotemporal substitution analysis was used to estimate model-predicted changes in CSH associated with reallocating time between movement behaviours. Predicted differences were generated using the sample composition and examined in 15-minute increments from −60 to +60 minutes for each behaviour. Two forms of reallocation were examined using the predict_delta_comps() function from the codaredistlm package in R. Proportional reallocations (comparisons = "prop-realloc") estimated the predicted change in CSH when time was added to or removed from one behaviour and redistributed proportionally across the remaining behaviours. One-versus-one reallocations (comparisons = "one-v-one") estimated the predicted change in CSH when time was exchanged directly between two behaviours while holding the remaining behaviours constant. All substitution models were adjusted for the same covariates used in the primary regression analyses (total wear time, sex, BMI, and age), with statistical significance evaluated at $\alpha = 0.05$.

## Results

A total of 101 shift-workers with complete data were included in the analytic sample. Participant characteristics, monitoring compliance, and composite sleep health (CSH) scores are shown in Table 7-2. Participants contributed an average of 6.7 (SD = 1.6) valid

monitoring days. The mean age was 41.0 (SD = 14.2) years, 63% of participants were women, and mean BMI was 28.2 (SD = 6.2) kg·m$^{-2}$. Average daily wear time was 1,014 minutes, with non-wear accounting for 2.5% of the day on average. Mean CSH was 3.0 (SD = 2.2) out of 10, indicating generally poor sleep health across the cohort.

*Table 7-2.*

*Participant Characteristics, Wear Compliance, and CSH*

| Variable | Mean (SD) or n (%) |
|---|---|
| Age, years | 41.0 (14.2) |
| Women | 64 (63%) |
| Men | 37 (37%) |
| BMI, kg·m$^{-2}$ | 28.2 (6.2) |
| Valid days, n | 6.7 (1.6) |
| Wear time, min·day$^{-1}$ | 1,014 (98.3) |
| Non-wear, percent of day | 2.5 (3.0) |
| Composite sleep health, 0–10 | 3.0 (2.2) |

Table 7-3 presents the mean daily 24-hour composition. Sedentary behaviour accounted for the largest proportion of the day, averaging 863.8 minutes/day (59.9%), followed by sleep at 413.6 minutes/day (28.7%). Participants accumulated an average of 82.0 minutes/day (5.6%) in LPA and 80.7 minutes/day (5.6%) in MVPA. These values represent the mean composition used in subsequent compositional analyses.

*Table 7-3.*

*Mean and Percentage of Time Spent in Each Activity Type per Day*

| 24-hour time-use composition | Compositional mean minutes/day (%) |
|---|---|
| Sedentary Behaviour | 863.78 (59.9) |
| Light Physical Activity | 81.97 (5.6) |
| Moderate to Vigorous Physical Activity | 80.69 (5.6) |
| Sleep | 413.56 28.7) |

## Compositional regression models

Table 7-4 presents the unadjusted and adjusted compositional regression models examining associations between the 24-hour movement composition and CSH. In unadjusted models, a greater relative proportion of sedentary behaviour was associated with lower CSH ($\beta = -3.3$, $p < .001$), while a greater relative proportion of sleep was associated with higher CSH ($\beta = 3.4$, $p < .001$). No significant associations were observed for LPA or MVPA.

After adjustment for total wear time, sex, BMI, and age, the associations for sedentary behaviour and sleep remained statistically significant. Greater relative sedentary behaviour was associated with lower CSH ($\beta = -7.2$, $p < .001$), whereas greater relative sleep was associated with higher CSH ($\beta = 8.2$, $p < .001$). Associations for LPA and MVPA remained non-significant in adjusted models ($p = .80$ and $p = .062$, respectively). The adjusted models explained 24.3% of the variance in CSH. The sensitivity analysis excluding sleep from the composition produced associations in similar directions to the primary analysis, with greater relative sedentary behaviour and MVPA associated with lower CSH, and greater relative LPA associated with higher CSH. However, these associations did not reach statistical significance and model explanatory power was lower (adjusted $R^2 = 0.144$), suggesting that sleep contributed substantially to the relationships observed in the primary compositional models (Appendix Table 6).

*Table 7-4.*

*Relationship Between Activity Intensity Compositions (Expressed as Isometric log-ratio Coordinates) and CSH*

| Isometric log-ratio predictor | Unadjusted model β – coefficient | P-value | Model $R^2$ | Adjusted model β – coefficient | P-value | Model $R^2$ |
|---|---|---|---|---|---|---|
| Ilr Sed/LightPA*MVPA*SLEEP | -3.3 | <0.001 | 0.134 | -7.2 | <0.001 | 0.243 |
| Ilr LightPA/Sed*MVPA*SLEEP | 0.62 | 0.400 | 0.134 | 0.20 | 0.80 | 0.243 |
| Ilr MVPA/Sed*LightPA*SLEEP | -0.66 | 0.30 | 0.134 | -1.2 | 0.062 | 0.243 |
| Ilr SLEEP/Sed*LightPA*MVPA | 3.4 | <0.001 | 0.134 | 8.2 | <0.001 | 0.243 |

Compositional isotemporal substitution analyses estimated the predicted change in CSH associated with reallocating time between behaviours while maintaining the total 24-hour composition. Reallocations were modelled in 15-minute increments from −60 to +60 minutes.

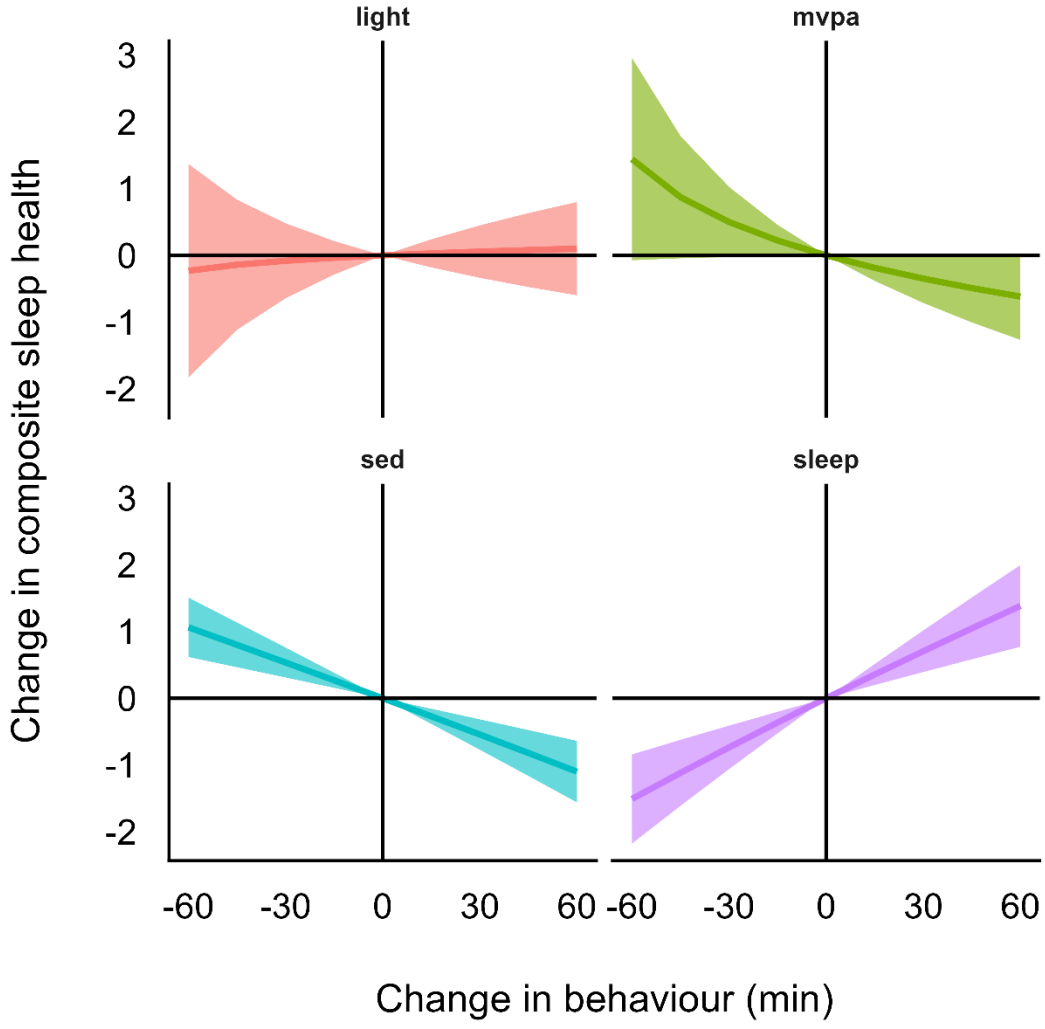
## Proportional Reallocations

Figure 7-1 presents the proportional reallocation models, where time added to or removed from one behaviour was redistributed proportionally across the remaining behaviours. Reallocations involving sedentary behaviour and sleep demonstrated the clearest associations with CSH. Reducing sedentary behaviour by 60 minutes, with time redistributed proportionally across LPA, MVPA, and sleep, was associated with a predicted increase in CSH of 1.06 units (95% CI 0.62 to 1.51). Smaller predicted increases were also observed for 45- and 30-minute reductions in sedentary behaviour.

Conversely, reducing sleep by 60 minutes and redistributing this time proportionally across sedentary behaviour, LPA, and MVPA was associated with a predicted decrease in CSH of 1.51 units (95% CI −2.18 to −0.84). Similar negative associations were observed for 45- and 30-minute reductions in sleep. Reallocations involving LPA or MVPA showed comparatively small predicted changes in CSH, with confidence intervals crossing zero across most reallocations examined. Full proportional reallocation estimates are presented in Appendix Table 6.

*Figure 7-1.*

*Proportional Reallocations (one-versus-many)*

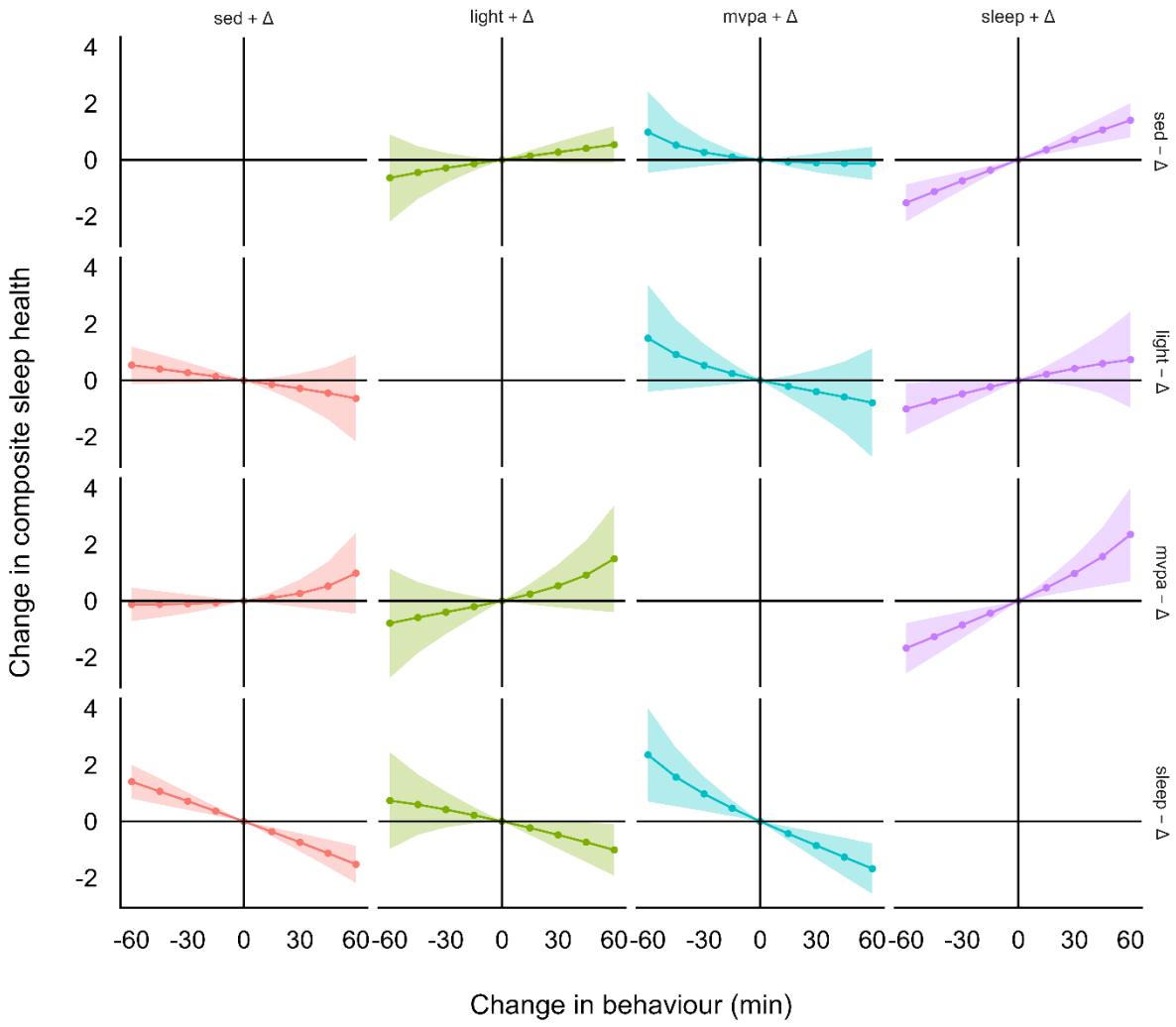


## One-versus-one reallocations

Figure 7-2 presents the one-versus-one isotemporal substitution models, where time was exchanged directly between pairs of behaviours while holding the remaining behaviours constant. Consistent with the proportional reallocation analyses, the largest predicted changes in CSH were observed for reallocations involving sedentary behaviour and sleep. Pairwise reallocations involving LPA or MVPA generally produced smaller and less precise predicted changes in CSH. Complete one-versus-one reallocation estimates are provided in Appendix Table 7.

*Figure 7-2.*

*One-versus-One Reallocations*



# Discussion

The present study examined how the relative distribution of daily time-use behaviours relates to composite sleep health (CSH) in shift-workers and estimated the predicted change in CSH associated with reallocating time across the 24-hour day. Using compositional data analysis and isotemporal substitution modelling, the findings suggest that the balance between sleep and sedentary behaviour was the dominant behavioural relationship associated with CSH in this cohort. Greater relative sleep was associated with higher CSH, whereas greater relative sedentary behaviour was associated with lower CSH. In contrast, LPA and MVPA showed little evidence of association with CSH.

These findings align with broader compositional research demonstrating that sleep and sedentary behaviour jointly contribute to health outcomes within constrained 24-hour movement compositions (Brakenridge et al., 2021; Curtis et al., 2023). The present study extends this literature into a shift-work context using fully objective measurement of both movement behaviours and multidimensional sleep health. Given that participants spent approximately 60% of the day sedentary and demonstrated generally poor sleep health, the findings suggest that the behavioural structure of shift-work may constrain opportunities for restorative sleep while simultaneously promoting prolonged sedentary exposure (Hulsegge et al., 2017).

The isotemporal substitution analyses reinforced this pattern. Reallocating time away from sedentary behaviour was associated with modest predicted improvements in CSH, particularly when redistributed towards sleep. Conversely, reallocating time away from sleep produced the largest predicted reductions in CSH. In comparison, reallocations involving LPA or MVPA showed comparatively small and imprecise predicted changes, with confidence intervals frequently crossing zero. These findings suggest that, within this cohort, preserving sleep opportunity may be more influential for multidimensional sleep health than increasing physical activity volume alone.

Several explanations may account for the limited associations observed for MVPA. First, the cohort accumulated relatively modest volumes of MVPA with limited variability, potentially restricting the detectable impact of reallocations involving higher-intensity

activity. Second, the accelerometer-derived MVPA measure did not distinguish between occupational and leisure-time activity. This may be relevant given evidence supporting the physical activity/health paradox, where occupational physical activity does not consistently produce the same health benefits as leisure-time activity. Finally, the timing of physical activity was not incorporated into the compositional models. Previous work suggests that the effects of physical activity on sleep may depend on both intensity and timing, particularly in shift-working populations exposed to circadian disruption (Stutz et al., 2019; Zapalac et al., 2024).

Taken together, these findings suggest that CSH in shift-workers may be more strongly influenced by the balance between sleep opportunity and sedentary exposure than by overall physical activity volume. Importantly, the findings should not be interpreted as suggesting that MVPA is unimportant for health, but rather that its relationship with multidimensional sleep health may be less pronounced within a cohort characterised by constrained schedules, high sedentary exposure, and generally poor sleep health. Within this context, reallocations that preserve or extend sleep opportunity may represent the most achievable behavioural target for improving sleep health.

## Strengths and limitations

This study has several limitations. The cross-sectional design prevents causal interpretation, and the monitoring period may not fully capture longer-term behavioural patterns or roster variability. Work schedule characteristics such as shift timing, shift length, commute duration, and roster structure were not directly modelled, limiting the ability to separate behavioural effects from schedule-driven effects. Similarly, contextual distinctions within behaviours, such as occupational versus leisure sedentary time or physical activity, were not available. The timing of movement behaviours was also not incorporated into the compositional models despite likely relevance for sleep outcomes in shift-workers. In addition, low variability in MVPA may have reduced the ability to detect associations involving higher-intensity activity. The categorical scoring approach used to derive CSH may reduce sensitivity to small differences in individual sleep dimensions.

Finally, because sleep contributed to both the predictor composition and the derivation of the CSH outcome, some conceptual overlap between exposure and outcome is unavoidable. A sensitivity analysis excluding sleep from the composition attenuated the observed associations and reduced model explanatory power, suggesting that sleep duration was an important driver of the primary findings. This is perhaps unsurprising given that CSH is intended to reflect multiple dimensions of sleep, including duration, timing, regularity, variability, and efficiency. The strong association between sleep duration and CSH therefore supports the construct validity of the outcome measure, while the broadly consistent directional associations observed in the sensitivity analysis suggest that the balance between sleep and waking behaviours may also be relevant to sleep health in shift-workers.

Despite these limitations, the study also demonstrated several strengths. A major strength was the use of device-derived 24-hour movement behaviours and objectively measured multidimensional sleep health collected concurrently within free-living conditions. Modelling the full 24-hour day as a composition aligns with contemporary movement-behaviour epidemiology and enables interpretation of behavioural trade-offs within a finite day (Dumuid et al., 2022a; Grgic et al., 2018). The application of compositional isotemporal substitution also strengthened interpretability by translating compositional relationships into estimated changes in CSH associated with realistic reallocations of time between behaviours.

## Conclusion

In conclusion, reallocations that increased sleep and reduced sedentary behaviour showed the clearest associations with improved composite sleep health in shift-workers. In contrast, reallocations involving LPA and MVPA demonstrated comparatively small and inconsistent associations. Within a cohort characterised by high sedentary exposure and poor sleep health, these findings suggest that protecting sleep opportunity and reducing prolonged sedentary time may represent more influential behavioural targets for supporting multidimensional sleep health in shift-workers. Future research should

incorporate behavioural timing, occupational context, and roster characteristics to further understand how 24-hour activity patterns influence sleep health within shift-working populations.

# Chapter 8 – General Discussion

The overall purpose of this thesis was to explore objectively measured, composite sleep health in the context of shift-workers by focusing on its measurement, distribution and exploring its associations with personal health views, practices, and 24-hour time use, ultimately yielding a characterisation of the relationship between sleep health and its behavioural correlates. This approach was intended to clarify how sleep health is embedded within the lived 24-hour routines of shift-workers and to identify where meaningful opportunities for improvement might exist. The remainder of this chapter summarises the key findings from each study, integrates them into several overarching themes, and discusses limitations, implications, and directions for future research in shift-workers.

## Research summary

Chapter 3 examined whether a wrist-validated sleep algorithm (van Hees et al., 2015) could be applied to mid-thigh and low-back accelerometers in free-living adults. Mid-thigh accelerometery showed the closest agreement with wrist-derived sleep estimates at both the epoch and nightly summary levels, whereas low-back estimates demonstrated weaker agreement and tended to overestimate sleep. These findings supported the use of mid-thigh accelerometery for deriving objective sleep metrics and provided the methodological foundation for the composite sleep health analyses used throughout the remainder of the thesis.

Chapter 4 investigated whether composite sleep health differed across work schedule groups, including daytime workers, shift-workers with nights, shift-workers without nights, and individuals with more personal than working days during monitoring. Daytime workers demonstrated the most favourable sleep health profiles, while night shift-workers displayed the poorest composite sleep health across multiple dimensions, including sleep duration, variability, efficiency, and timing. Despite these group differences, poor

composite sleep health was common across the cohort, indicating a broader burden of impaired sleep health within this shift-working population.

Chapter 5 examined associations between objectively measured composite sleep health and self-reported health and well-being outcomes, including stress, burnout, resilience, depressive symptoms, and sleeping troubles. Composite sleep health showed only weak associations with psychosocial outcomes and only approached statistical significance for subjective sleeping troubles. Overall, objective sleep health appeared to capture a dimension of vulnerability that was not strongly reflected in broad self-reported well-being measures.

Chapter 6 explored whether self-reported lifestyle behaviours, including physical activity, dietary behaviours, caffeine use, alcohol consumption, smoking, and sleep aid use, explained variation in composite sleep health among shift-workers. Most behaviours showed little association with composite sleep health. After adjustment for age, gender, and BMI, only caffeine use remained significantly associated with composite sleep health but explained only a modest proportion of variance. These findings suggest that conventional lifestyle behaviours account for only a limited component of sleep health variability in shift-workers.

Chapter 7 examined how the composition of the 24-hour day, including sleep, sedentary behaviour, light physical activity, and moderate-to-vigorous physical activity, related to composite sleep health. More sedentary-dominant daily compositions were associated with poorer composite sleep health, whereas sleep-dominant compositions were associated with more favourable sleep health. Isotemporal substitution modelling suggested that reallocating time from sedentary behaviour toward sleep was associated with predicted improvements in composite sleep health, while reductions in sleep were associated with poorer outcomes. These findings positioned composite sleep health within the broader behavioural context of constrained 24-hour time use in shift-workers.

## Significance of findings

### Advancing the objective measurement of composite sleep health

A major contribution of this thesis is the demonstration that composite sleep health (CSH) can be derived from thigh-worn accelerometery within a real-world occupational setting using existing open-source methods. Chapter 3 established the methodological foundation for the subsequent studies by showing that sleep metrics derived from mid-thigh accelerometery using the wrist-validated van Hees algorithm showed acceptable agreement with wrist-derived estimates at the group level. Compared with the low-back placement, the mid-thigh produced more comparable estimates of sleep timing, duration, efficiency, and awakenings, supporting its use for objective CSH assessment throughout the remainder of the thesis.

This finding is important because most accelerometery-based sleep research has relied on wrist-worn devices, whereas thigh-worn accelerometers have traditionally been used to characterise posture and sedentary behaviour rather than sleep (Johansson et al., 2023; Suorsa et al., 2020). At the same time, integrated 24-hour movement research increasingly requires methods capable of simultaneously capturing sleep, sedentary behaviour, and physical activity within a single behavioural framework (Dumuid et al., 2020). The present thesis extends this work by demonstrating that a single thigh-worn device can provide usable estimates of both sleep and waking behaviours in free-living conditions, allowing sleep health to be examined within the broader context of 24-hour time use.

The decision to adopt a thigh-based approach also aligned with the broader aims of the thesis. Because the same device was used to derive both waking behaviour and sleep metrics, it was possible to apply a consistent, objective CSH metric across Chapters 4 to 7 while minimising participant burden and maintaining ecological validity in a shift-working population. This approach is particularly relevant in occupational research, where highly controlled laboratory methods such as polysomnography are often impractical and where behavioural monitoring must occur within complex operational environments.

Importantly, the objective CSH metric used throughout this thesis was conceptually grounded in Buysse's multidimensional sleep health framework (Buysse, 2014). The composite incorporated accelerometery-derived indicators of sleep duration, timing, efficiency, regularity, and variability, allowing multiple dimensions of sleep to be captured simultaneously within an entirely objective framework. While subjective dimensions such as satisfaction and alertness were not included, this reflected the practical realities of device-based monitoring rather than a departure from the broader sleep health construct (Ravyts et al., 2021). In this context, the inclusion of variability as an additional objective indicator was particularly relevant for shift-workers, whose sleep patterns are often characterised by substantial night-to-night instability.

Overall, this thesis demonstrates that thigh-worn accelerometery can support the objective assessment of composite sleep health within integrated 24-hour behavioural research. This provides a practical and scalable approach for future occupational and epidemiological studies seeking to examine sleep, sedentary behaviour, and physical activity simultaneously within real-world settings.

## Poor sleep health as a systemic feature of shift-work

A central finding of this thesis was that poor composite sleep health (CSH) was pervasive across the shift-working cohort, regardless of specific schedule classification. Although Chapter 4 demonstrated clear differences between groups, with daytime workers showing the most favourable sleep profiles and night shift-workers the poorest, low CSH scores were observed across nearly all schedule types. Even workers without extensive night duties or with more personal days than workdays during monitoring frequently demonstrated short, irregular, and inefficient sleep. Collectively, these findings suggest that poor sleep health in this cohort was not confined solely to permanent night work but instead reflected a broader pattern of chronic sleep disruption embedded within the occupational environment.

This pattern aligns with a substantial body of shift-work literature demonstrating that irregular schedules, circadian disruption, and constrained recovery opportunities

contribute to shortened sleep, greater sleep variability, and persistent fatigue (Härmä et al., 2019; Kalmbach et al., 2018; Kecklund & Axelsson, 2016). However, the present thesis extends this literature by applying an objectively derived multidimensional sleep health framework rather than relying on individual sleep metrics or subjective sleep complaints alone. The uniformly poor distribution of CSH scores observed across Chapters 4 to 7 suggests that many workers were simultaneously experiencing disruptions across multiple dimensions of sleep, including duration, timing, efficiency, regularity, and variability. This is important because composite sleep health frameworks emphasise that sleep disruption rarely occurs in isolation, and that cumulative deficits across dimensions may better reflect real-world sleep-related risk (Buysse, 2014; Ravyts et al., 2021).

The findings also suggest that poor sleep health in shift-workers may be better understood as a systemic rather than purely individual problem. Shift-work inherently disrupts alignment between biological circadian rhythms and socially imposed schedules, often requiring workers to obtain sleep at biologically suboptimal times (Reutrakul & Knutson, 2015; Vetter, 2020). In addition to schedule-related disruption, workers may experience ongoing "social jetlag," where sleep timing remains misaligned with both endogenous circadian rhythms and social or family obligations (Hulsegge et al., 2019; Wittmann et al., 2006). These competing demands likely constrain opportunities for stable and restorative sleep, even outside of night-shift periods. From this perspective, the widespread nature of poor CSH observed in this thesis reflects broader structural and organisational pressures operating across the 24-hour day rather than simply poor individual sleep habits.

Importantly, the pervasive nature of poor CSH also provides context for interpreting the later chapters of the thesis. Associations between CSH and psychosocial outcomes, lifestyle behaviours, and 24-hour movement compositions were all examined within a cohort already characterised by chronically poor sleep health. This compressed distribution may partly explain why many observed associations were relatively modest. At the same time, the consistently low CSH scores reinforce the view that this workforce represents a high-risk sleep environment in which poor sleep health has become normalised.

Overall, this thesis demonstrates that poor composite sleep health is widespread across shift-working schedules and appears to reflect systemic features of shift-working environments rather than isolated sleep problems within specific worker groups. These findings suggest that interventions narrowly focused on individual behaviour change or on permanent night workers alone are unlikely to address the full burden of sleep disruption. Instead, improving sleep health in shift-workers may require broader organisational approaches that consider roster design, recovery opportunity, circadian disruption, and the structural constraints shaping behaviour across the 24-hour day.

## Objective sleep health and subjective health are distinct constructs

Another important finding of this thesis was that objectively measured composite sleep health (CSH) showed relatively weak relationships with most self-reported health, well-being, and lifestyle measures. Across Chapters 5 and 6, poorer objective CSH was not strongly associated with general health ratings, resilience, burnout, depressive symptoms, or most self-reported health behaviours. The clearest relationships emerged only for subjective sleeping troubles and caffeine intake, where poorer objective sleep health coincided with greater perceived sleep-related difficulties and lower caffeine intake. Collectively, these findings suggest that objectively disrupted sleep patterns do not necessarily translate into a broad perception of being unhealthy or psychologically distressed within this shift-working cohort.

This finding contrasts with much of the broader sleep literature, where poor sleep is commonly associated with poorer self-rated health, fatigue, emotional distress, and reduced well-being (Lekander et al., 2013; Perry et al., 2013; Ursin et al., 2005). However, many of these studies rely on subjective measures of sleep duration, sleep quality, insomnia symptoms, or perceived sleep need rather than objective multidimensional sleep metrics. When both the exposure and outcome are self-reported, stronger associations may partly reflect shared appraisal processes and common method variance (Podsakoff et al., 2024; Spector et al., 2019). In contrast, the present thesis used an

entirely objective CSH metric derived from accelerometery, allowing sleep behaviour to be examined independently of how participants perceived or evaluated their own sleep.

The weak relationships observed in this thesis therefore suggest that objective sleep disruption and subjective health appraisal may represent partially distinct constructs in shift-workers. Workers with chronically poor sleep may adapt to, normalise, or under-recognise their sleep disruption, particularly within occupational cultures where fatigue and irregular sleep are viewed as expected components of the job (Caudwell et al., 2020). From this perspective, poor sleep health may exist as a chronic background condition that does not consistently trigger perceptions of ill-health or motivate substantial changes in self-reported health behaviours. The finding that sleeping troubles remained associated with objective CSH supports this interpretation, as sleep-specific symptoms may represent a more direct and salient signal that sleep is failing to meet perceived needs.

This interpretation is also consistent with behavioural frameworks such as the theory of planned behaviour and the related concept of perceived need (Payne et al., 2004). These models suggest that individuals are more likely to prioritise behaviour change when they perceive a problem as personally relevant or requiring action. In the context of shift-work, chronically disrupted sleep may become sufficiently normalised that workers no longer interpret it as an urgent health concern, even when objective sleep health is poor. Emerging work examining dysfunctional sleep beliefs in shift-workers similarly suggests that attitudes, beliefs, and perceived necessity surrounding sleep may strongly influence how workers interpret and respond to chronic sleep disruption (Song et al., 2025).

The findings of this thesis therefore should not be interpreted as evidence that objective CSH lacks health relevance. Rather, they suggest that objective sleep disruption alone may be insufficient to explain how workers perceive their health, evaluate their well-being, or engage with health-related behaviours. Objective sleep metrics capture patterns of sleep timing, duration, regularity, and efficiency, but they do not necessarily capture whether workers perceive those patterns as problematic, meaningful, or requiring intervention. This distinction may help explain why objective CSH showed only weak relationships with broader psychosocial and behavioural measures in this cohort. These weak associations may also partly reflect methodological factors, including measurement error inherent in

accelerometery-derived sleep estimates, the influence of threshold selection when classifying sleep health, and restricted variability in sleep health within the cohort, which may have attenuated the observed relationships.

## Sleep health within a constrained 24-hour behavioural system

The findings of this thesis also highlight the importance of understanding sleep health within the broader context of 24-hour behaviour and the structural constraints imposed by shift-work. Across Chapters 6 and 7, composite sleep health (CSH) appeared to be shaped less by isolated lifestyle behaviours and more by the distribution of time and recovery opportunities across the day. While most self-reported health behaviours showed only weak associations with CSH, the compositional analyses in Chapter 7 demonstrated that more sedentary-dominant daily compositions were associated with poorer sleep health, whereas compositions with greater sleep opportunity were associated with more favourable CSH outcomes.

These findings align with contemporary time-use epidemiology, which conceptualises sleep, sedentary behaviour, and physical activity as interdependent components of a finite 24-hour day (Dumuid et al., 2018; Pedišić, 2014). Within this framework, increasing time in one behaviour necessarily reduces time available for another. The isotemporal substitution models used in Chapter 7 suggested that reallocating time away from sedentary behaviour and towards sleep was associated with predicted improvements in CSH, whereas reducing sleep opportunity to increase other behaviours was associated with poorer sleep health. Collectively, these findings reinforce the idea that sleep opportunity itself may represent one of the most important behavioural resources available to shift-workers.

Importantly, the findings also suggest that conventional assumptions surrounding "healthy behaviours" may not translate straightforwardly into shift-working environments. In Chapter 6, greater total physical activity energy expenditure was not associated with CSH, a finding that appears counterintuitive when considered alongside broader physical activity literature. However, this pattern is consistent with the growing

“physical activity/health paradox,” where high levels of occupational physical activity may contribute to fatigue, physiological strain, and insufficient recovery rather than improved health outcomes (Hallman et al., 2017; Wang et al., 2025). In shift-working populations, total physical activity volume may therefore reflect occupational load and constrained recovery opportunities rather than discretionary or restorative exercise behaviour.

Similarly, the positive association observed between caffeine use and CSH likely reflects the complex role of caffeine within fatigue management rather than a direct sleep-promoting effect. Caffeine is widely used operationally to maintain alertness and performance under conditions of sleep restriction and extended wakefulness, despite its well-established capacity to impair sleep when consumed close to bedtime (Drake et al., 2013). Within this cohort, caffeine use may therefore represent a strategic coping mechanism among workers with relatively better managed sleep patterns, rather than a simple marker of unhealthy behaviour.

Taken together, these findings suggest that improving sleep health in shift-workers may depend less on increasing overall behavioural demands and more on protecting and stabilising sleep opportunity within an already constrained 24-hour system. In practical terms, reallocating time from sedentary wakefulness towards sleep may represent a more realistic and achievable intervention target than expecting workers to substantially increase structured exercise participation alongside demanding and fatiguing schedules. This interpretation is consistent with broader shift-work intervention literature, which increasingly emphasises the importance of scheduling, recovery opportunity, sleep timing, and fatigue management strategies over isolated behaviour change approaches (Easton et al., 2024; Shriane et al., 2020).

## Strengths, limitations, and future directions

This thesis has several important strengths. A major strength was the use of an objective, multidimensional CSH metric applied consistently across multiple studies within the same shift-working cohort. Rather than relying on single sleep metrics or subjective sleep reports alone, the thesis incorporated accelerometery-derived indicators of sleep

duration, timing, efficiency, regularity, and variability, allowing sleep health to be examined as a multidimensional construct grounded in contemporary sleep health frameworks (Buysse, 2014; Ravyts et al., 2021). The use of thigh-worn accelerometery further enabled the simultaneous assessment of sleep, sedentary behaviour, and physical activity within a single 24-hour behavioural framework, supporting integrated analyses of time use in free-living conditions.

Another strength was the ecological validity of the research design. Data were collected within a real-world operational setting across both work and non-workdays, allowing sleep and behavioural patterns to be examined within the context of everyday shift-working life rather than under highly controlled laboratory conditions. The thesis also integrated several analytical approaches, including objective sleep assessment, psychosocial measures, behavioural analyses, and compositional data analysis, providing a broader and more systems-oriented understanding of sleep health in shift-workers. From an applied perspective, this work is important for occupational health practitioners and organisations that may be required to make decisions in real-world settings, where sleep, fatigue, roster demands, recovery opportunity, and health behaviours occur simultaneously rather than as isolated exposures.

Several limitations should nevertheless be acknowledged. First, the sleep metrics used to derive CSH were generated from thigh-worn accelerometery processed using a wrist-validated algorithm that was not specifically re-parameterised for thigh-derived data. Although Chapter 3 demonstrated acceptable agreement at the group level, some residual bias likely remained, particularly for individual-level estimates. The approach was adopted because few open-source alternatives currently exist for thigh-based sleep assessment, and because the broader aim of the thesis was to explore the feasibility of integrating sleep and waking behaviour assessment within a single-device framework.

Second, CSH scores were consistently low across the cohort, resulting in a relatively compressed distribution of sleep health. This likely introduced some degree of range restriction, which may have attenuated observable associations between CSH and psychosocial or behavioural outcomes in later chapters. However, modifying scoring thresholds post hoc was considered inappropriate, as the thresholds were intentionally

grounded in established sleep health recommendations rather than adjusted to fit a chronically sleep-disrupted population. Additionally, the compressed distribution is itself informative, as it suggests that poor multidimensional sleep health may be sufficiently widespread in shift-working contexts that it becomes difficult to distinguish higher-risk workers using subjective health indicators or isolated metrics alone.

Finally, the thesis focused on workers from a single organisation within one industry. While this provided a relatively coherent operational context and strengthened internal consistency across studies, it may limit generalisability to other occupational settings or forms of shift-work. Nevertheless, many of the broader patterns observed in this thesis are consistent with findings reported in other shift-working populations, including healthcare and military cohorts (Furihata et al., 2020; Härmä et al., 2019; Seelig et al., 2016). These findings then also point towards the value of context-sensitive sleep-health assessment, where the practical focus is not only on whether shift-workers sleep enough, but on how work schedules, daily behaviour patterns, and subjective perceptions combine to shape whether restorative sleep is realistically achievable.

Several important directions for future research emerge from this work. Future studies should continue refining and validating sleep detection approaches for thigh-worn accelerometery, including the development or re-parameterisation of algorithms specifically designed for thigh-derived sleep signals. Longitudinal studies following workers across multiple roster cycles, industries, locations and cultures would also provide greater insight into how composite sleep health fluctuates in response to changing schedules, recovery opportunities, and behavioural patterns over time. Future research should also examine whether combining sleep dimensions into a single equally weighted CSH score, offers benefits beyond examining the dimensions individually, including whether some dimensions are more strongly associated with health outcomes than others.

Future research would additionally benefit from integrating objective sleep assessment with measures of perceived sleep need, sleep beliefs, fatigue appraisal, and organisational culture. The findings of this thesis suggest that objective sleep disruption may not always

align with subjective perceptions of health or sleep-related risk, highlighting the need to better understand how workers interpret and respond to chronic sleep disruption.

Finally, future compositional and behavioural work should move beyond examining the total volume of behaviours alone and instead consider the timing and context in which behaviours occur. This would provide a strong extension of the 24-hour movement-behaviour framework. In particular, examining when sedentary behaviour, physical activity, caffeine use, and recovery opportunities occur relative to sleep windows may provide a more nuanced understanding of how daily routines influence sleep health. In shift-workers, this approach may help clarify whether sleep health is associated with the broader distribution of daily behaviour, rather than only with volumetric totals. Together, these directions would further strengthen the development of integrated, objective, and context-sensitive approaches to sleep health research in occupational settings.

## Overall Conclusion

This thesis examined how objectively measured composite sleep health (CSH) relates to health perceptions, lifestyle behaviours, and 24-hour time use within a real-world shift-working cohort using accelerometery-based monitoring. Collectively, the findings demonstrate that thigh-worn accelerometery can support the objective assessment of multidimensional sleep health within integrated 24-hour behavioural research. Across the cohort, poor CSH was pervasive and extended beyond permanent night shift-workers, suggesting that chronic sleep disruption is a broader systemic feature of shift-working environments.

Despite this widespread burden of objectively poor sleep health, CSH showed only weak relationships with most self-reported psychosocial outcomes and lifestyle behaviours, indicating that objective sleep disruption and subjective health appraisal may represent partially distinct constructs in shift-workers. At the same time, the compositional analyses demonstrated that sleep health exists within a constrained 24-hour behavioural system, where protecting sleep opportunity, particularly through reductions in sedentary wake time, may represent one of the most practical avenues for improving sleep health.

Overall, this thesis contributes to the growing field of multidimensional sleep health by demonstrating the feasibility and value of objective, integrated sleep assessment within occupational settings. The findings highlight the importance of viewing sleep health not simply as an individual behaviour, but as a phenomenon shaped by organisational structures, behavioural trade-offs, and the realities of working across the 24-hour day.

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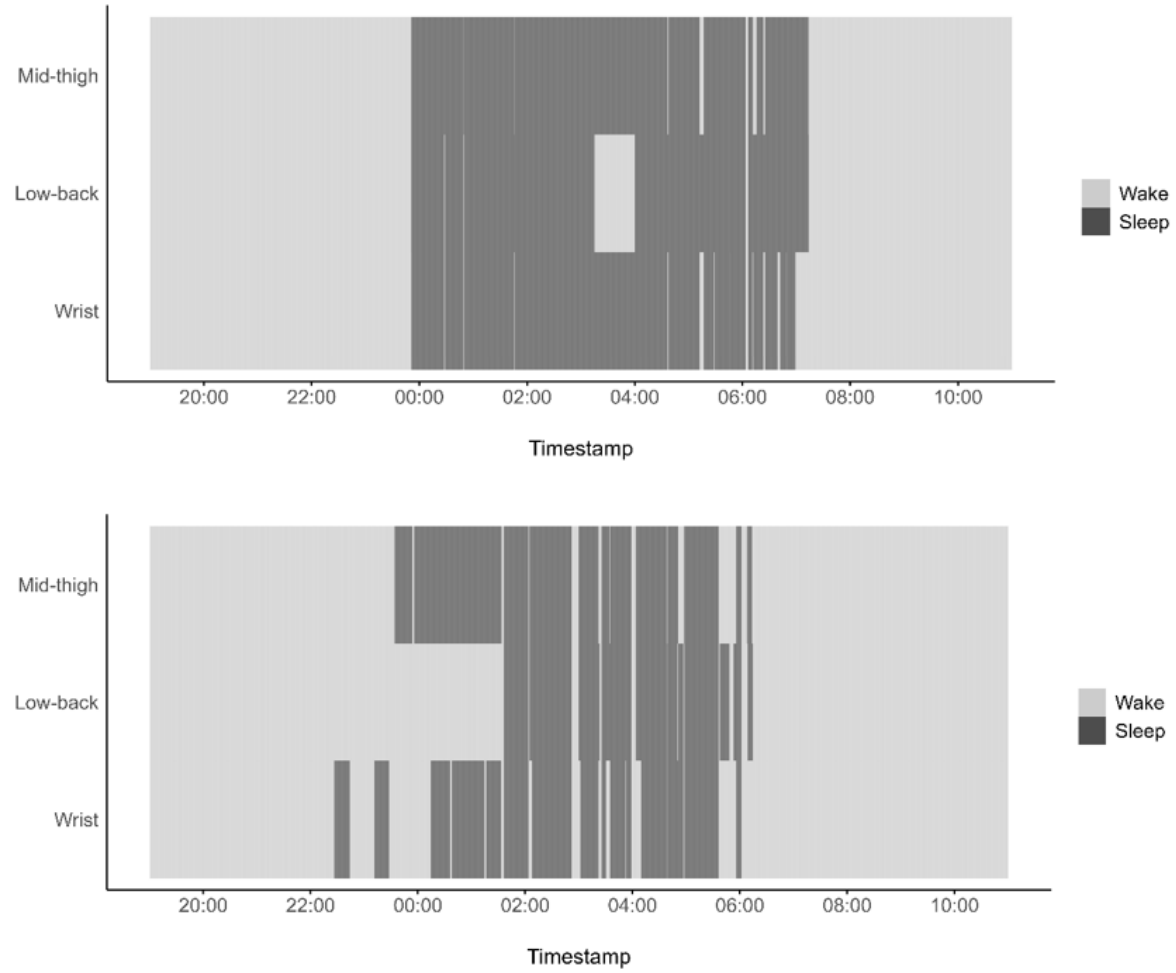
Zhang, S., Zhang, M., Yuan, Y., Li, Z., Li, X., & Li, X. (2025). Health risks and genetic architecture of objectively measured multidimensional sleep health. *Nature Communications*, *16*(1), 7026. https://doi.org/10.1038/s41467-025-62338-0

# Appendices

## Appendix A – Supplementary Material for Chapter 3

*Appendix Figure 1.*

*Visual Discrepancy Outliers*



*Appendix Table 1.*

*Configuration Settings Used for Accelerometer Data Processing*

| Argument | Value | Context |
|---|---|---|
| datadir | C:/Users/gpassfie/OneDrive - AUT University/Geoff/PhD/Research Studies/Study 1A/Results Raw Thigh-back-wrist correlation study | not applicable |
| do.report | c(2,4,5) | not applicable |
| f0 | 1 | not applicable |
| f1 | 61 | not applicable |
| mode | c(1,2,3,4,5) | not applicable |
| outputdir | C:/users/gpassfie/OneDrive - AUT University/Geoff/PhD/Research Studies/Study 1A | not applicable |
| studyname | c() | not applicable |
| GGIRread_version | 0.3.0 | not applicable |
| GGIRversion | 2.10.1 | not applicable |
| R_version | R version 4.3.1 (2023-06-16 ucrt) | not applicable |
| qwindow | c(0,24) | params_247 |
| qlevels | c() | params_247 |
| qwindow_dateformat | %d-%m-%Y | params_247 |
| ilevels | c() | params_247 |
| IVIS_windowsize_minutes | 60 | params_247 |
| IVIS_epochsize_seconds | c() | params_247 |
| IVIS.activity.metric | 2 | params_247 |
| IVIS_acc_threshold | 20 | params_247 |
| qM5L5 | c() | params_247 |
| MX.ig.min.dur | 10 | params_247 |
| M5L5res | 10 | params_247 |
| winhr | 5 | params_247 |
| iglevels | c() | params_247 |
| LUXthresholds | c(0,100,500,1000,3000,5000,10000) | params_247 |
| LUX_cal_constant | c() | params_247 |
| LUX_cal_exponent | c() | params_247 |
| LUX_day_segments | c() | params_247 |
| window.summary.size | 10 | params_247 |
| L5M5window | c(0,24) | params_247 |
| cosinor | FALSE | params_247 |
| includedaycrit | 16 | params_cleaning |
| ndayswindow | 7 | params_cleaning |
| strategy | 1 | params_cleaning |
| maxdur | 0 | params_cleaning |
| hrs.del.start | 0 | params_cleaning |
| hrs.del.end | 0 | params_cleaning |
| includedaycrit.part5 | 0.666667 | params_cleaning |

| | | |
|---|---|---|
| excludefirstlast.part5 | FALSE | params_cleaning |
| TimeSegments2ZeroFile | c() | params_cleaning |
| do.imp | TRUE | params_cleaning |
| data_cleaning_file | c() | params_cleaning |
| minimum_MM_length.part5 | 23 | params_cleaning |
| excludefirstlast | FALSE | params_cleaning |
| includenightcrit | 16 | params_cleaning |
| excludefirst.part4 | FALSE | params_cleaning |
| excludelast.part4 | FALSE | params_cleaning |
| max_calendar_days | 0 | params_cleaning |
| nonWearEdgeCorrection | TRUE | params_cleaning |
| nonwear_approach | 2013 | params_cleaning |
| segmentWEARcrit.part5 | 0.5 | params_cleaning |
| segmentDAYSPTcrit.part5 | c(0,0) | params_cleaning |
| overwrite | FALSE | params_general |
| acc.metric | ENMO | params_general |
| maxNcores | c() | params_general |
| print.filename | FALSE | params_general |
| do.parallel | TRUE | params_general |
| windowsizes | c(5,900,3600) | params_general |
| desiredtz | | params_general |
| configtz | c() | params_general |
| idloc | 1 | params_general |
| dayborder | 0 | params_general |
| part5_agg2_60seconds | FALSE | params_general |
| sensor.location | wrist | params_general |
| expand_tail_max_hours | c() | params_general |
| recordingEndSleepHour | c() | params_general |
| dataFormat | raw | params_general |
| maxRecordingInterval | c() | params_general |
| extEpochData_timeformat | %d-%m-%Y %H:%M:%S | params_general |
| do.anglex | FALSE | params_metrics |
| do.angley | FALSE | params_metrics |
| do.anglez | TRUE | params_metrics |
| do.zcx | FALSE | params_metrics |
| do.zcy | FALSE | params_metrics |
| do.zcz | FALSE | params_metrics |
| do.enmo | TRUE | params_metrics |
| do.lfenmo | FALSE | params_metrics |
| do.en | FALSE | params_metrics |
| do.mad | FALSE | params_metrics |
| do.enmoa | FALSE | params_metrics |
| do.roll_med_acc_x | FALSE | params_metrics |
| do.roll_med_acc_y | FALSE | params_metrics |
| do.roll_med_acc_z | FALSE | params_metrics |

| | | |
|---|---|---|
| do.dev_roll_med_acc_x | FALSE | params_metrics |
| do.dev_roll_med_acc_y | FALSE | params_metrics |
| do.dev_roll_med_acc_z | FALSE | params_metrics |
| do.bfen | FALSE | params_metrics |
| do.hfen | FALSE | params_metrics |
| do.hfenplus | FALSE | params_metrics |
| do.lfen | FALSE | params_metrics |
| do.lfx | FALSE | params_metrics |
| do.lfy | FALSE | params_metrics |
| do.lfz | FALSE | params_metrics |
| do.hfx | FALSE | params_metrics |
| do.hfy | FALSE | params_metrics |
| do.hfz | FALSE | params_metrics |
| do.bfx | FALSE | params_metrics |
| do.bfy | FALSE | params_metrics |
| do.bfz | FALSE | params_metrics |
| do.brondcounts | FALSE | params_metrics |
| do.neishabouricounts | FALSE | params_metrics |
| hb | 15 | params_metrics |
| lb | 0.2 | params_metrics |
| n | 4 | params_metrics |
| zc.lb | 0.25 | params_metrics |
| zc.hb | 3 | params_metrics |
| zc.sb | 0.01 | params_metrics |
| zc.order | 2 | params_metrics |
| zc.scale | 1 | params_metrics |
| actilife_LFE | FALSE | params_metrics |
| epochvalues2csv | FALSE | params_output |
| save_ms5rawlevels | FALSE | params_output |
| save_ms5raw_format | csv | params_output |
| save_ms5raw_without_invalid | TRUE | params_output |
| storefolderstructure | FALSE | params_output |
| timewindow | c(MM,WW) | params_output |
| viewingwindow | 1 | params_output |
| dofirstpage | TRUE | params_output |
| visualreport | TRUE | params_output |
| week_weekend_aggregate.part5 | FALSE | params_output |
| do.part3.pdf | TRUE | params_output |
| outliers.only | FALSE | params_output |
| criterror | 3 | params_output |
| do.visual | TRUE | params_output |
| do.sibreport | FALSE | params_output |
| do.part2.pdf | TRUE | params_output |
| sep_reports | , | params_output |
| sep_config | , | params_output |

| visualreport_without_invalid | TRUE | params_output |
|---|---|---|
| mvpathreshold | 100 | params_phyact |
| boutcriter | 0.8 | params_phyact |
| mvpadur | c(1,5,10) | params_phyact |
| boutcriter.in | 0.9 | params_phyact |
| boutcriter.lig | 0.8 | params_phyact |
| boutcriter.mvpa | 0.8 | params_phyact |
| threshold.lig | 40 | params_phyact |
| threshold.mod | 100 | params_phyact |
| threshold.vig | 400 | params_phyact |
| boutdur.mvpa | c(1,5,10) | params_phyact |
| boutdur.in | c(10,20,30) | params_phyact |
| boutdur.lig | c(1,5,10) | params_phyact |
| frag.metrics | c() | params_phyact |
| chunksize | 1 | params_rawdata |
| spherecrit | 0.3 | params_rawdata |
| minloadcrit | 72 | params_rawdata |
| printsummary | FALSE | params_rawdata |
| do.cal | TRUE | params_rawdata |
| backup.cal.coef | retrieve | params_rawdata |
| dynrange | c() | params_rawdata |
| minimumFileSizeMB | 2 | params_rawdata |
| rmc.dec | . | params_rawdata |
| rmc.firstrow.acc | c() | params_rawdata |
| rmc.firstrow.header | c() | params_rawdata |
| rmc.header.length | c() | params_rawdata |
| rmc.col.acc | c(1,2,3) | params_rawdata |
| rmc.col.temp | c() | params_rawdata |
| rmc.col.time | c() | params_rawdata |
| rmc.unit.acc | g | params_rawdata |
| rmc.unit.temp | C | params_rawdata |
| rmc.unit.time | POSIX | params_rawdata |
| rmc.format.time | %Y-%m-%d %H:%M:%OS | params_rawdata |
| rmc.bitrate | c() | params_rawdata |
| rmc.dynamic_range | c() | params_rawdata |
| rmc.unsignedbit | TRUE | params_rawdata |
| rmc.origin | ######## | params_rawdata |
| rmc.desiredtz | c() | params_rawdata |
| rmc.configtz | c() | params_rawdata |
| rmc.sf | c() | params_rawdata |
| rmc.headername.sf | c() | params_rawdata |
| rmc.headername.sn | c() | params_rawdata |
| rmc.headername.recordingid | c() | params_rawdata |
| rmc.header.structure | c() | params_rawdata |
| rmc.check4timegaps | FALSE | params_rawdata |

| | | |
|---|---|---|
| rmc.noise | 13 | params_rawdata |
| rmc.col.wear | c() | params_rawdata |
| rmc.doresample | FALSE | params_rawdata |
| interpolationType | 1 | params_rawdata |
| imputeTimegaps | TRUE | params_rawdata |
| frequency_tol | 0.1 | params_rawdata |
| anglethreshold | 5 | params_sleep |
| timethreshold | 5 | params_sleep |
| ignorenonwear | TRUE | params_sleep |
| constrain2range | TRUE | params_sleep |
| HASPT.algo | HDCZA | params_sleep |
| HASIB.algo | vanHees2015 | params_sleep |
| Sadeh_axis | | params_sleep |
| longitudinal_axis | c() | params_sleep |
| HASPT.ignore.invalid | FALSE | params_sleep |
| loglocation | c() | params_sleep |
| colid | 1 | params_sleep |
| coln1 | 2 | params_sleep |
| nnights | c() | params_sleep |
| relyonguider | FALSE | params_sleep |
| def.noc.sleep | 1 | params_sleep |
| sleeplogsep | c() | params_sleep |
| sleepwindowType | SPT | params_sleep |

*Appendix Table 2.*

*Bland Altman and Pearson Correlation Values, Mid-thigh Compared to Wrist*

| N=20 | Mid-thigh compared to wrist | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Bias | 95% CI | Lower LoA | 95% CI | Upper LoA | 95% CI | r | p | 95% CI |
| TST, min | 6.91 | -2.68, 16.50 | -33.25 | -49.91,-16.6 | 47.06 | 30.40, 63.70 | 0.94 | <0.001 | 0.86, 0.98 |
| WASO, min | 3.70 | -11.50, 4.05 | -36.17 | -49.70,-22.70 | 28.76 | 15.30, 42.24 | 0.86 | <0.001 | 0.68, 0.94 |
| SE, % | 0.86 | -0.68, 2.40 | -5.59 | -8.27,-2.91 | 7.31 | 4.63, 9.98 | 0.86 | <0.001 | 0.68, 0.95 |
| AWK, n | -2.40 | -3.84, -0.96 | -8.45 | -10.96,-5.94 | 3.65 | 1.14, 6.16 | 0.86 | <0.001 | 0.66, 0.94 |
| SI, min | 3.20 | -3.82, 10.20 | -26.23 | -38.45,-14.00 | 32.64 | 20.42, 44.90 | 0.98 | <0.001 | 0.94, 0.99 |
| SOT difference, min | -3.04 | -8.78, 2.70 | -27.07 | -37.05,-17.10 | 21.00 | 11.02, 30.97 | 0.97 | <0.001 | 0.92, 0.99 |

*Appendix Table 3.*

*Bland Altman and Pearson Correlation Values, Low-back Compared to Wrist*

| N=20 | Low-back compared to wrist | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Bias | 95% CI | Lower LoA | 95% CI | Upper LoA | 95% CI | r | p | 95% CI |
| TST, min | 22.50 | 11.50, 33.40 | -23.30 | -42.3, -4.32 | 68.3 | 49.30, 87.28 | 0.92 | < 0.001 | 0.82, 0.97 |
| WASO, min | -14.80 | -23.53, -60 | -51.50 | -66.75, -36.26 | 22.00 | 6.71, 37.20 | 0.81 | < 0.001 | 0.56, 0.92 |
| SE, % | 3.28 | 1.42, 5.14 | -4.51 | -7.74, -1.27 | 11.08 | 7.84, 14.31 | 0.78 | < 0.001 | 0.51, 0.91 |
| AWK, n | -3.45 | -5.85, -1.05 | -13.49 | -17.66, -9.32 | 6.59 | 2.42, 10.76 | 0.63 | < 0.003 | 0.26, 0.84 |
| SI, min | 7.70 | 1.04, 14.36 | -20.19 | -31.77, -8.62 | 35.59 | 24.02, 47.17 | 0.98 | < 0.001 | 0.95, 0.99 |
| SOT difference, min | -6.15 | -11.79, -0.51 | -29.75 | -39.55, -19.96 | 17.45 | 7.66, 27.25 | 0.97 | < 0.001 | 0.92, 0.99 |

# Appendix B – Supplementary Material for Chapter 5

As a result of the non-significant findings of > 3 nights of sleep data model, a second, more relaxed inclusion criterion (nights of sleep data > 1) was run to investigate the impact on the results. This expanded the sample size to 99 participants. However, similar to the previous model, composite sleep health did not significantly predict most of the examined outcomes.

*Appendix Table 4.*

*Unadjusted Model of Shift-workers With More Than 1 Night of Sleep Data*

| Parameter | n | Coefficient Unstandardised β | SE | Lower CL | Upper CL | p | $R^2$ |
|---|---|---|---|---|---|---|---|
| Unadjusted models[1] | | | | | | | |
| Brief Resilience Scale | 99 | .046 | .230 | -.410 | .502 | .843 | .000 |
| General Health perception | 99 | -.067 | .048 | -.162 | .029 | .171 | .019 |
| Sleeping Troubles (subjective) | 99 | -2.085 | 1.084 | -4.236 | .066 | .057 | .036 |
| Burnout | 99 | -.434 | 1.059 | -2.536 | 1.668 | .682 | .002 |
| Stress | 99 | -.091 | 1.122 | -2.317 | 2.135 | .935 | .000 |
| Depressive symptoms | 99 | -.242 | .917 | -2.061 | 1.577 | .792 | .001 |
| Somatic Stress | 99 | .390 | .826 | -1.249 | 2.029 | .638 | .002 |
| Cognitive Stress | 99 | .428 | .862 | -1.282 | 2.138 | .621 | .003 |

# Appendix C – Supplementary Material for Chapter 7

*Appendix Table 5.*

*Configuration Settings Used for Accelerometer Data Processing*

| Argument | Value | Context |
|---|---|---|
| config_file_in_outputdir | output/output_to_process/config.csv | not applicable |
| datadir | to_process | not applicable |
| do.report | c(4,5) | not applicable |
| f0 | 1 | not applicable |
| f1 | 125 | not applicable |
| LC_TIME_backup | English_New Zealand.utf8 | not applicable |
| mode | c(3,4,5) | not applicable |
| outputdir | output | not applicable |
| studyname | c() | not applicable |
| GGIRread_version | 1.0.5 | not applicable |
| GGIRversion | 3.3.0 | not applicable |
| R_version | R version 4.5.1 (2025-06-13 ucrt) | not applicable |
| qwindow | c(0,24) | params_247 |
| qlevels | c() | params_247 |
| qwindow_dateformat | %d-%m-%Y | params_247 |
| ilevels | c() | params_247 |
| IVIS_windowsize_minutes | 60 | params_247 |
| IVIS_epochsize_seconds | c() | params_247 |
| IVIS.activity.metric | 2 | params_247 |
| IVIS_acc_threshold | 20 | params_247 |
| qM5L5 | c() | params_247 |
| MX.ig.min.dur | 10 | params_247 |
| M5L5res | 10 | params_247 |
| winhr | 5 | params_247 |
| iglevels | c() | params_247 |
| LUXthresholds | c(0,100,500,1000,3000,5000,10000) | params_247 |
| LUX_cal_constant | c() | params_247 |
| LUX_cal_exponent | c() | params_247 |
| LUX_day_segments | c() | params_247 |
| L5M5window | c(0,24) | params_247 |
| cosinor | FALSE | params_247 |
| part6CR | FALSE | params_247 |

| | | |
|---|---|---|
| part6HCA | FALSE | params_247 |
| part6Window | c(start,end) | params_247 |
| part6DFA | FALSE | params_247 |
| clevels | c(30,150) | params_247 |
| SRI2_WASOmin | 30 | params_247 |
| includedaycrit | 16 | params_cleaning |
| ndayswindow | 7 | params_cleaning |
| strategy | 1 | params_cleaning |
| data_masking_strategy | 1 | params_cleaning |
| maxdur | 0 | params_cleaning |
| hrs.del.start | 0 | params_cleaning |
| hrs.del.end | 0 | params_cleaning |
| includedaycrit.part5 | 0.666666666666667 | params_cleaning |
| excludefirstlast.part5 | FALSE | params_cleaning |
| TimeSegments2ZeroFile | c() | params_cleaning |
| do.imp | TRUE | params_cleaning |
| data_cleaning_file | c() | params_cleaning |
| minimum_MM_length.part5 | 23 | params_cleaning |
| excludefirstlast | FALSE | params_cleaning |
| includenightcrit | 16 | params_cleaning |
| excludefirst.part4 | FALSE | params_cleaning |
| excludelast.part4 | FALSE | params_cleaning |
| max_calendar_days | 0 | params_cleaning |
| nonWearEdgeCorrection | TRUE | params_cleaning |
| nonwear_approach | 2023 | params_cleaning |
| segmentWEARcrit.part5 | 0.5 | params_cleaning |
| segmentDAYSPTcrit.part5 | c(0.9,0) | params_cleaning |
| study_dates_file | c() | params_cleaning |
| study_dates_dateformat | %d-%m-%Y | params_cleaning |
| includecrit.part6 | c(0.666666666666667,0.666666666666667) | params_cleaning |
| includenightcrit.part5 | 0 | params_cleaning |
| nonwearFiltermaxHours | c() | params_cleaning |
| nonwearFilterWindow | c() | params_cleaning |
| overwrite | TRUE | params_general |
| acc.metric | ENMO | params_general |
| maxNcores | c() | params_general |
| print.filename | TRUE | params_general |
| do.parallel | FALSE | params_general |

| | | |
|---|---|---|
| windowsizes | c(5,900,3600) | params_general |
| desiredtz | NZ | params_general |
| configtz | NZ | params_general |
| idloc | 6 | params_general |
| dayborder | 0 | params_general |
| part5_agg2_60seconds | FALSE | params_general |
| sensor.location | wrist | params_general |
| expand_tail_max_hours | c() | params_general |
| recordingEndSleepHour | c() | params_general |
| dataFormat | raw | params_general |
| maxRecordingInterval | c() | params_general |
| extEpochData_timeformat | %d-%m-%Y %H:%M:%S | params_general |
| recording_split_times | c() | params_general |
| recording_split_timeformat | %d/%m/%Y %H:%M | params_general |
| recording_split_overlap | 0 | params_general |
| recording_split_ignore_edges | FALSE | params_general |
| do.anglex | FALSE | params_metrics |
| do.angley | FALSE | params_metrics |
| do.anglez | TRUE | params_metrics |
| do.zcx | FALSE | params_metrics |
| do.zcy | FALSE | params_metrics |
| do.zcz | FALSE | params_metrics |
| do.enmo | TRUE | params_metrics |
| do.lfenmo | FALSE | params_metrics |
| do.en | FALSE | params_metrics |
| do.mad | FALSE | params_metrics |
| do.enmoa | FALSE | params_metrics |
| do.roll_med_acc_x | FALSE | params_metrics |
| do.roll_med_acc_y | FALSE | params_metrics |
| do.roll_med_acc_z | FALSE | params_metrics |
| do.dev_roll_med_acc_x | FALSE | params_metrics |
| do.dev_roll_med_acc_y | FALSE | params_metrics |
| do.dev_roll_med_acc_z | FALSE | params_metrics |
| do.bfen | FALSE | params_metrics |
| do.hfen | FALSE | params_metrics |
| do.hfenplus | FALSE | params_metrics |
| do.lfen | FALSE | params_metrics |
| do.lfx | FALSE | params_metrics |

| | | |
|---|---|---|
| do.lfy | FALSE | params_metrics |
| do.lfz | FALSE | params_metrics |
| do.hfx | FALSE | params_metrics |
| do.hfy | FALSE | params_metrics |
| do.hfz | FALSE | params_metrics |
| do.bfx | FALSE | params_metrics |
| do.bfy | FALSE | params_metrics |
| do.bfz | FALSE | params_metrics |
| do.brondcounts | FALSE | params_metrics |
| do.neishabouricounts | FALSE | params_metrics |
| hb | 15 | params_metrics |
| lb | 0.2 | params_metrics |
| n | 4 | params_metrics |
| zc.lb | 0.25 | params_metrics |
| zc.hb | 3 | params_metrics |
| zc.sb | 0.01 | params_metrics |
| zc.order | 2 | params_metrics |
| zc.scale | 1 | params_metrics |
| actilife_LFE | FALSE | params_metrics |
| epochvalues2csv | FALSE | params_output |
| save_ms5rawlevels | TRUE | params_output |
| save_ms5raw_format | RData | params_output |
| save_ms5raw_without_invalid | FALSE | params_output |
| storefolderstructure | FALSE | params_output |
| timewindow | c(MM,WW) | params_output |
| viewingwindow | 1 | params_output |
| dofirstpage | TRUE | params_output |
| visualreport | FALSE | params_output |
| week_weekend_aggregate.part5 | FALSE | params_output |
| do.part3.pdf | FALSE | params_output |
| outliers.only | FALSE | params_output |
| criterror | 3 | params_output |
| do.visual | TRUE | params_output |
| do.sibreport | TRUE | params_output |
| do.part2.pdf | TRUE | params_output |
| sep_reports | , | params_output |
| sep_config | , | params_output |
| dec_reports | . | params_output |

| | | |
|---|---|---|
| dec_config | . | params_output |
| visualreport_without_invalid | TRUE | params_output |
| old_visualreport | FALSE | params_output |
| visualreport_hrsPerRow | 36 | params_output |
| visualreport_focus | day | params_output |
| visualreport_validcrit | 0 | params_output |
| require_complete_lastnight_part5 | FALSE | params_output |
| method_research_vars | c() | params_output |
| mvpathreshold | 100 | params_phyact |
| boutcriter | 0.8 | params_phyact |
| mvpadur | c(1,5,10) | params_phyact |
| boutcriter.in | 0.9 | params_phyact |
| boutcriter.lig | 0.8 | params_phyact |
| boutcriter.mvpa | 0.8 | params_phyact |
| threshold.lig | 40 | params_phyact |
| threshold.mod | 100 | params_phyact |
| threshold.vig | 400 | params_phyact |
| boutdur.mvpa | c(1,5,10) | params_phyact |
| boutdur.in | c(10,20,30) | params_phyact |
| boutdur.lig | c(1,5,10) | params_phyact |
| frag.metrics | c() | params_phyact |
| part6_threshold_combi | 40_100_400 | params_phyact |
| chunksize | 1 | params_rawdata |
| spherecrit | 0.3 | params_rawdata |
| minloadcrit | 168 | params_rawdata |
| printsummary | FALSE | params_rawdata |
| do.cal | TRUE | params_rawdata |
| backup.cal.coef | retrieve | params_rawdata |
| dynrange | c() | params_rawdata |
| minimumFileSizeMB | 2 | params_rawdata |
| rmc.dec | . | params_rawdata |
| rmc.firstrow.acc | c() | params_rawdata |
| rmc.firstrow.header | c() | params_rawdata |
| rmc.header.length | c() | params_rawdata |
| rmc.col.acc | c(1,2,3) | params_rawdata |
| rmc.col.temp | c() | params_rawdata |
| rmc.col.time | c() | params_rawdata |
| rmc.unit.acc | g | params_rawdata |

| | | |
|---|---|---|
| rmc.unit.temp | C | params_rawdata |
| rmc.unit.time | POSIX | params_rawdata |
| rmc.format.time | %Y-%m-%d %H:%M:%OS | params_rawdata |
| rmc.bitrate | c() | params_rawdata |
| rmc.dynamic_range | c() | params_rawdata |
| rmc.unsignedbit | TRUE | params_rawdata |
| rmc.origin | 1970-01-01 | params_rawdata |
| rmc.desiredtz | c() | params_rawdata |
| rmc.configtz | c() | params_rawdata |
| rmc.sf | c() | params_rawdata |
| rmc.headername.sf | c() | params_rawdata |
| rmc.headername.sn | c() | params_rawdata |
| rmc.headername.recordingid | c() | params_rawdata |
| rmc.header.structure | c() | params_rawdata |
| rmc.check4timegaps | FALSE | params_rawdata |
| rmc.noise | 13 | params_rawdata |
| nonwear_range_threshold | 150 | params_rawdata |
| rmc.col.wear | c() | params_rawdata |
| rmc.doresample | FALSE | params_rawdata |
| interpolationType | 1 | params_rawdata |
| imputeTimegaps | TRUE | params_rawdata |
| frequency_tol | 0.1 | params_rawdata |
| rmc.scalefactor.acc | 1 | params_rawdata |
| anglethreshold | 5 | params_sleep |
| timethreshold | 5 | params_sleep |
| ignorenonwear | TRUE | params_sleep |
| HASPT.algo | HDCZA | params_sleep |
| HASIB.algo | vanHees2015 | params_sleep |
| Sadeh_axis | | params_sleep |
| longitudinal_axis | c() | params_sleep |
| HASPT.ignore.invalid | FALSE | params_sleep |
| loglocation | sleep_log.csv | params_sleep |
| colid | 1 | params_sleep |
| coln1 | 2 | params_sleep |
| nnights | c() | params_sleep |
| relyonguider | FALSE | params_sleep |
| def.noc.sleep | 1 | params_sleep |
| sleeplogsep | c() | params_sleep |

| | | |
|---|---|---|
| sleepwindowType | TimeInBed | params_sleep |
| possible_nap_window | c() | params_sleep |
| possible_nap_dur | c() | params_sleep |
| possible_nap_gap | 0 | params_sleep |
| possible_nap_edge_acc | Inf | params_sleep |
| nap_model | c() | params_sleep |
| sleepefficiency.metric | 1 | params_sleep |
| HDCZA_threshold | c() | params_sleep |
| oakley_threshold | 20 | params_sleep |
| consider_marker_button | FALSE | params_sleep |
| impute_marker_button | FALSE | params_sleep |
| sib_must_fully_overlap_with_TimeInBed | c(TRUE,TRUE) | params_sleep |
| nap_markerbutton_method | 0 | params_sleep |
| nap_markerbutton_max_distance | 30 | params_sleep |
| SRI1_smoothing_wsize_hrs | c() | params_sleep |
| SRI1_smoothing_frac | c() | params_sleep |
| spt_min_block_dur | 30 | params_sleep |
| spt_max_gap_dur | 60 | params_sleep |
| spt_max_gap_ratio | 1 | params_sleep |
| HorAngle_threshold | 60 | params_sleep |
| guider_cor_maxgap_hrs | 2 | params_sleep |
| guider_cor_min_frac_sib | 0.5 | params_sleep |
| guider_cor_min_hrs | 2 | params_sleep |
| guider_cor_meme_frac_out | 0.9 | params_sleep |
| guider_cor_meme_frac_in | 0.4 | params_sleep |
| guider_cor_meme_min_hrs | 1 | params_sleep |
| guider_cor_do | FALSE | params_sleep |
| guider_cor_meme_min_dys | 3 | params_sleep |

*Appendix Table 6.*

*Relationship Between Activity Compositions (with sleep removed) and CSH*

| Isometric log-ratio predictor | Unadjusted model β – coefficient | P-value | Model $R^2$ | Adjusted model β – coefficient | P-value | Model $R^2$ |
|---|---|---|---|---|---|---|
| Ilr Sed/LightPA*MVPA | -0.80 | 0.20 | 0.026 | -0.82 | 0.20 | 0.144 |
| Ilr LightPA/Sed*MVPA | 1.10 | 0.20 | 0.026 | 1.10 | 0.20 | 0.144 |
| Ilr MVPA/Sed*LightPA | -0.32 | 0.70 | 0.026 | -0.27 | 0.70 | 0.144 |

*Appendix Table 7.*

*Isotemporal Substitution Estimates for Reallocations Around the Sample Composition*

| Activity altered and reallocated proportionally | Time reallocated | Predicted difference in CSH (β) | 95% Confidence Interval, low | 95% Confidence Interval, high | Statistical significance |
|---|---|---|---|---|---|
| sed | -60 | 1.06 | 0.62 | 1.51 | * |
| light | -60 | -0.23 | -1.83 | 1.37 | |
| mvpa | -60 | 1.44 | -0.07 | 2.96 | |
| sleep | -60 | -1.51 | -2.18 | -0.84 | * |
| sed | -45 | 0.80 | 0.46 | 1.13 | * |
| light | -45 | -0.14 | -1.11 | 0.83 | |
| mvpa | -45 | 0.87 | -0.04 | 1.79 | |
| sleep | -45 | -1.12 | -1.61 | -0.62 | * |
| sed | -30 | 0.53 | 0.31 | 0.76 | * |
| light | -30 | -0.08 | -0.64 | 0.48 | |
| mvpa | -30 | 0.50 | -0.03 | 1.02 | |
| sleep | -30 | -0.74 | -1.06 | -0.41 | * |
| sed | -15 | 0.27 | 0.16 | 0.38 | * |
| light | -15 | -0.04 | -0.29 | 0.21 | |
| mvpa | -15 | 0.22 | -0.01 | 0.46 | |
| sleep | -15 | -0.36 | -0.52 | -0.20 | * |
| sed | 0 | 0.00 | 0.00 | 0.00 | |
| light | 0 | 0.00 | 0.00 | 0.00 | |
| mvpa | 0 | 0.00 | 0.00 | 0.00 | |
| sleep | 0 | 0.00 | 0.00 | 0.00 | |
| sed | 15 | -0.27 | -0.38 | -0.16 | * |
| light | 15 | 0.03 | -0.18 | 0.24 | |
| mvpa | 15 | -0.19 | -0.38 | 0.01 | |
| sleep | 15 | 0.36 | 0.20 | 0.51 | * |
| sed | 30 | -0.54 | -0.77 | -0.32 | * |
| light | 30 | 0.06 | -0.34 | 0.45 | |
| mvpa | 30 | -0.35 | -0.71 | 0.02 | |
| sleep | 30 | 0.70 | 0.39 | 1.02 | * |
| sed | 45 | -0.82 | -1.16 | -0.48 | * |
| light | 45 | 0.08 | -0.47 | 0.63 | |
| mvpa | 45 | -0.49 | -1.00 | 0.02 | |
| sleep | 45 | 1.05 | 0.58 | 1.51 | * |
| sed | 60 | -1.10 | -1.56 | -0.64 | * |
| light | 60 | 0.10 | -0.60 | 0.80 | |
| mvpa | 60 | -0.62 | -1.27 | 0.03 | |
| sleep | 60 | 1.38 | 0.77 | 1.99 | * |

*Appendix Table 8.*

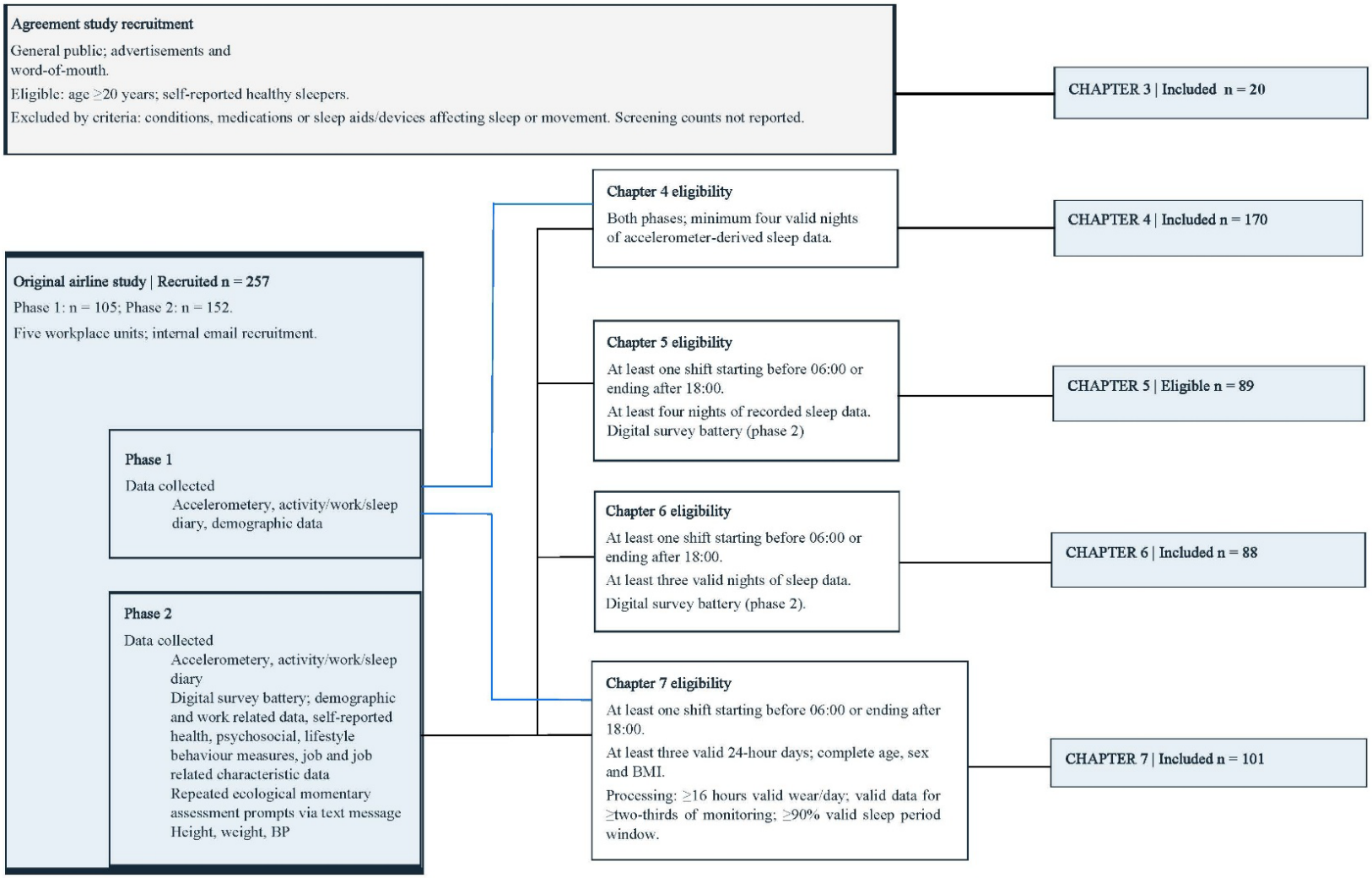
*One-versus-one Isotemporal Substitution Estimates for Reallocations Around the Sample Composition*

| Activity decreased | Activity increased | Time reallocated | Predicted difference in CSH (β) | 95% CI, low | 95% CI, high | Statistical significance |
|---|---|---|---|---|---|---|
| sed | light | -60 | 0.43 | -0.17 | 1.04 | |
| sed | mvpa | -60 | -0.14 | -0.68 | 0.41 | |
| sed | sleep | -60 | 1.13 | 0.57 | 1.69 | * |
| light | sed | -60 | -0.52 | -1.95 | 0.91 | |
| light | mvpa | -60 | -0.68 | -2.47 | 1.11 | |
| light | sleep | -60 | 0.59 | -1.00 | 2.18 | |
| mvpa | sed | -60 | 0.88 | -0.46 | 2.22 | |
| mvpa | light | -60 | 1.29 | -0.46 | 3.04 | |
| mvpa | sleep | -60 | 1.99 | 0.45 | 3.52 | * |
| sleep | sed | -60 | -1.23 | -1.84 | -0.62 | * |
| sleep | light | -60 | -0.82 | -1.66 | 0.03 | |
| sleep | mvpa | -60 | -1.39 | -2.22 | -0.56 | * |
| sed | light | -45 | 0.33 | -0.16 | 0.81 | |
| sed | mvpa | -45 | -0.13 | -0.56 | 0.30 | |
| sed | sleep | -45 | 0.85 | 0.43 | 1.28 | * |
| light | sed | -45 | -0.36 | -1.23 | 0.50 | |
| light | mvpa | -45 | -0.51 | -1.67 | 0.66 | |
| light | sleep | -45 | 0.48 | -0.51 | 1.47 | |
| mvpa | sed | -45 | 0.48 | -0.32 | 1.27 | |
| mvpa | light | -45 | 0.79 | -0.35 | 1.93 | |
| mvpa | sleep | -45 | 1.32 | 0.36 | 2.27 | * |
| sleep | sed | -45 | -0.91 | -1.36 | -0.46 | * |
| sleep | light | -45 | -0.60 | -1.25 | 0.06 | |
| sleep | mvpa | -45 | -1.05 | -1.69 | -0.41 | * |
| sed | light | -30 | 0.22 | -0.12 | 0.56 | |
| sed | mvpa | -30 | -0.11 | -0.42 | 0.20 | |
| sed | sleep | -30 | 0.57 | 0.29 | 0.86 | * |
| light | sed | -30 | -0.23 | -0.73 | 0.26 | |
| light | mvpa | -30 | -0.35 | -1.06 | 0.37 | |
| light | sleep | -30 | 0.34 | -0.25 | 0.92 | |
| mvpa | sed | -30 | 0.25 | -0.21 | 0.70 | |
| mvpa | light | -30 | 0.46 | -0.25 | 1.16 | |
| mvpa | sleep | -30 | 0.81 | 0.25 | 1.38 | * |
| sleep | sed | -30 | -0.60 | -0.90 | -0.30 | * |
| sleep | light | -30 | -0.39 | -0.84 | 0.07 | |
| sleep | mvpa | -30 | -0.71 | -1.15 | -0.27 | * |
| sed | light | -15 | 0.11 | -0.07 | 0.29 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| sed | mvpa | -15 | -0.07 | -0.23 | 0.10 | |
| sed | sleep | -15 | 0.29 | 0.15 | 0.43 | * |
| light | sed | -15 | -0.11 | -0.33 | 0.11 | |
| light | mvpa | -15 | -0.18 | -0.52 | 0.16 | |
| light | sleep | -15 | 0.18 | -0.09 | 0.44 | |
| mvpa | sed | -15 | 0.10 | -0.10 | 0.30 | |
| mvpa | light | -15 | 0.21 | -0.13 | 0.55 | |
| mvpa | sleep | -15 | 0.39 | 0.13 | 0.65 | * |
| sleep | sed | -15 | -0.30 | -0.44 | -0.15 | * |
| sleep | light | -15 | -0.19 | -0.42 | 0.05 | |
| sleep | mvpa | -15 | -0.36 | -0.59 | -0.13 | * |
| sed | light | 0 | 0.00 | 0.00 | 0.00 | |
| sed | mvpa | 0 | 0.00 | 0.00 | 0.00 | |
| sed | sleep | 0 | 0.00 | 0.00 | 0.00 | |
| light | sed | 0 | 0.00 | 0.00 | 0.00 | |
| light | mvpa | 0 | 0.00 | 0.00 | 0.00 | |
| light | sleep | 0 | 0.00 | 0.00 | 0.00 | |
| mvpa | sed | 0 | 0.00 | 0.00 | 0.00 | |
| mvpa | light | 0 | 0.00 | 0.00 | 0.00 | |
| mvpa | sleep | 0 | 0.00 | 0.00 | 0.00 | |
| sleep | sed | 0 | 0.00 | 0.00 | 0.00 | |
| sleep | light | 0 | 0.00 | 0.00 | 0.00 | |
| sleep | mvpa | 0 | 0.00 | 0.00 | 0.00 | |
| sed | light | 15 | -0.11 | -0.33 | 0.11 | |
| sed | mvpa | 15 | 0.10 | -0.10 | 0.30 | |
| sed | sleep | 15 | -0.30 | -0.44 | -0.15 | * |
| light | sed | 15 | 0.11 | -0.07 | 0.29 | |
| light | mvpa | 15 | 0.21 | -0.13 | 0.55 | |
| light | sleep | 15 | -0.19 | -0.42 | 0.05 | |
| mvpa | sed | 15 | -0.07 | -0.23 | 0.10 | |
| mvpa | light | 15 | -0.18 | -0.52 | 0.16 | |
| mvpa | sleep | 15 | -0.36 | -0.59 | -0.13 | * |
| sleep | sed | 15 | 0.29 | 0.15 | 0.43 | * |
| sleep | light | 15 | 0.18 | -0.09 | 0.44 | |
| sleep | mvpa | 15 | 0.39 | 0.13 | 0.65 | * |
| sed | light | 30 | -0.23 | -0.73 | 0.26 | |
| sed | mvpa | 30 | 0.25 | -0.21 | 0.70 | |
| sed | sleep | 30 | -0.60 | -0.90 | -0.30 | * |
| light | sed | 30 | 0.22 | -0.12 | 0.56 | |
| light | mvpa | 30 | 0.46 | -0.25 | 1.16 | |
| light | sleep | 30 | -0.39 | -0.84 | 0.07 | |
| mvpa | sed | 30 | -0.11 | -0.42 | 0.20 | |
| mvpa | light | 30 | -0.35 | -1.06 | 0.37 | |
| mvpa | sleep | 30 | -0.71 | -1.15 | -0.27 | * |
| sleep | sed | 30 | 0.57 | 0.29 | 0.86 | * |

| | | | | | | |
|---|---|---|---|---|---|---|
| sleep | light | 30 | 0.34 | -0.25 | 0.92 | |
| sleep | mvpa | 30 | 0.81 | 0.25 | 1.38 | * |
| sed | light | 45 | -0.36 | -1.23 | 0.50 | |
| sed | mvpa | 45 | 0.48 | -0.32 | 1.27 | |
| sed | sleep | 45 | -0.91 | -1.36 | -0.46 | * |
| light | sed | 45 | 0.33 | -0.16 | 0.81 | |
| light | mvpa | 45 | 0.79 | -0.35 | 1.93 | |
| light | sleep | 45 | -0.60 | -1.25 | 0.06 | |
| mvpa | sed | 45 | -0.13 | -0.56 | 0.30 | |
| mvpa | light | 45 | -0.51 | -1.67 | 0.66 | |
| mvpa | sleep | 45 | -1.05 | -1.69 | -0.41 | * |
| sleep | sed | 45 | 0.85 | 0.43 | 1.28 | * |
| sleep | light | 45 | 0.48 | -0.51 | 1.47 | |
| sleep | mvpa | 45 | 1.32 | 0.36 | 2.27 | * |
| sed | light | 60 | -0.52 | -1.95 | 0.91 | |
| sed | mvpa | 60 | 0.88 | -0.46 | 2.22 | |
| sed | sleep | 60 | -1.23 | -1.84 | -0.62 | * |
| light | sed | 60 | 0.43 | -0.17 | 1.04 | |
| light | mvpa | 60 | 1.29 | -0.46 | 3.04 | |
| light | sleep | 60 | -0.82 | -1.66 | 0.03 | |
| mvpa | sed | 60 | -0.14 | -0.68 | 0.41 | |
| mvpa | light | 60 | -0.68 | -2.47 | 1.11 | |
| mvpa | sleep | 60 | -1.39 | -2.22 | -0.56 | * |
| sleep | sed | 60 | 1.13 | 0.57 | 1.69 | * |
| sleep | light | 60 | 0.59 | -1.00 | 2.18 | |
| sleep | mvpa | 60 | 1.99 | 0.45 | 3.52 | * |

Appendix D – Participant sampling schematic across Chapters 4–7.



# Appendix E – Ethical Approval Letters


## Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics


10 September 2018

Lisa Mackay
Faculty of Health and Environmental Sciences

Dear Lisa

Re Ethics Application: **18/293 Understanding job demands and recovery from work**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 10 September 2021.

**Standard Conditions of Approval**

1. A progress report is due annually on the anniversary of the approval date, using form EA2, which is available online through http://www.aut.ac.nz/research/researchethics.
2. A final report is due at the expiration of the approval period, or, upon completion of project, using form EA3, which is available online through http://www.aut.ac.nz/research/researchethics.
3. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form: http://www.aut.ac.nz/research/researchethics.
4. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
5. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.

Please quote the application number and title on all future correspondence related to this project.

AUTEC grants ethical approval only. If you require management approval for access for your research from another institution or organisation, then you are responsible for obtaining it. You are reminded that it is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard.

For any enquiries, please contact ethics@aut.ac.nz

Yours sincerely,



Kate O'Connor
Executive Manager
**Auckland University of Technology Ethics Committee**

Cc: anantha.narayanan.tl@aut.ac.nz; Tom Stewart; scott.duncan@aut.ac.nz

15 November 2022

Grant Schofield

Faculty of Health and Environmental Sciences

Dear Grant

Re Ethics Application: **22/300 Validation of dual location accelerometers for sleep detection and monitoring**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 10 November 2025.

## Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard and that all the dates on the documents are updated.
8. AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat

Auckland University of Technology Ethics Committee

Cc: geoff.passfield@aut.ac.nz; lisa.mackay@aut.ac.nz; tom.stewart@aut.ac.nz; ccrofts@aut.ac.nz