Title: Use of the Sonomat for Evaluating Nocturnal Body Movements in Children.

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Statement Of Authorship and Originality

This is to certify, that the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

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I, Mimi Han Qing Lu, was first author and corresponding author for the following manuscript contained within the body of this thesis:

<u>Chapter 2</u> of this thesis has been published as a manuscript with the following full citation

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I performed literature review, drafted the initial manuscript and revised the manuscript with input from co-authors. In addition to the authorship attribution statements above, in cases where I am not the corresponding author of a published item, permission to include the published material has been granted by the corresponding author

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Abbreviations

ABBREVIATION	MEANING
AASM	American Academy of Sleep Medicine
ACT	Mean Percentage of Activity Per Minute Of Sleep (Actigraphy Metric)
ADHD	Attention-Deficit/Hyperactivity Disorder
AHI	Apnoea–Hypopneas Index
ALTE	Apparent Life-Threatening Event
AS	Active Sleep (Infant REM-Like Sleep)
BMI	Body Mass Index
CI	Confidence Interval
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
EMM	Estimated Marginal Means
EOG	Electro-Oculogram
GM	Gross Movements
ICC	Intraclass Correlation Coefficient
IDA	Iron Deficiency Anemia
IQR	Interquartile Range
IRA	Inter-Rater Agreement
IRLSSG	International Restless Legs Syndrome Study Group
LMM	Large Muscle Movements
MAT	Sonomat (Contactless Mattress Sensor)
MD	Movement Duration
$MD_{sleep\text{-}only}$	Movement Duration During PSG-Defined Sleep
MEI	Movement Event Index
MI	Movement Index
$MI_{sleep\text{-}only}$	Movement Index During PSG-Defined Sleep
MOAHI	Mixed Obstructive Apnoea–hypopneas Index
MT	Movement Time
NREM	Non–Rapid Eye Movement (Sleep Stage)
OSA	Obstructive Sleep Apnoea
OSAS	Obstructive Sleep Apnoea Syndrome
PLM	Periodic Limb Movement
PLMS	Periodic Limb Movements In Sleep
PSG	Polysomnography
REM	Rapid Eye Movement (Sleep Stage)
RLS	Restless Legs Syndrome
RMS	Root-Mean-Square
RSD	Restless Sleep Disorder
SCSB	Static Charge Sensitive Bed
SD	Standard Deviation
SDB	Sleep-Disordered Breathing
SIDS	Sudden Infant Death Syndrome
SM	Small Movements
TIB	Time In Bed
TSP	Total Sleep Period
TST	Total Sleep Time
TWT	Total Wake Time
vPSG	Video Polysomnography (video-only movement scoring)
Video/PSG	Video+Polysomnography scoring of movements

Abstract

Movements during sleep are routinely observed but they are not consistently quantified as part of a routine paediatric sleep assessment. This thesis reviews the historical and contemporary approaches to measuring body movements during sleep and evaluates the Sonomat (MAT) alongside polysomnography (PSG) as methods for quantifying sleep-related body movements. In a retrospective cohort of children who underwent concurrent Sonomat and PSG studies, movements were scored using multiple event-duration thresholds (≥ 1 s, ≥ 3 s, ≥ 5 s, ≥ 7 s). Movement index (MI, events/h) and movement duration (MD, % of time) were determined. Analyses included determining the agreement between the two study modalities and automated analysis algorithms were also examined. The final analysis explored whether the movement burden differed by obstructive sleep apnoea (OSA) status, and within a group of children with McGill oximetry scores of 1.

The Sonomat consistently measured higher MI and MD compared to PSG, detecting a greater number of small and brief movements than video/PSG . This difference diminished and lost statistical significance for MI when analysing only individual movements ≥7 s. Although MD remained statistically significant, the clinical relevance of a 0.9% difference (equivalent to 4.5 minutes of median total sleep period) is unclear. At the ≥3 s threshold for individual movements, inter-system agreement reached 88%. Movement duration emerged as the preferred burden metric, being less sensitive to event-splitting or merging than event-level metrics such as MI. Automated movement scoring on the MAT system showed asymmetry, with MD most closely approximating manual scoring, and an internal algorithm better reflecting manual scoring patterns.

Movement burden, especially MD, strongly correlated with wakefulness. We found no discrimination in movement metrics by OSA status in either overall scoring or sleep-restricted analyses. The small cohort size and retrospective study design limited statistical power for detailed sub-analyses, including stratification within the McGill score 1 group. Additionally, sleep disordered breathing manifesting as snoring or stertor is captured by the Sonomat, but not captured by mixed obstructive apnoea-hypopnoea index (MOAHI).

In summary, the Sonomat is a viable tool for measuring body movements during sleep detecting a greater number of brief movements than PSG but convergence with PSG for events ≥7 s. Movement duration (MD) provides a more robust measure of movement burden with better comparability across scoring modalities than MI. Movement metrics strongly tracked wakefulness but in our small cohort did not differentiate OSA status as defined by MOAHI. Future research directions include analysing wake versus sleep states based on Sonomat movement characteristics, assessing differences using sleep disordered breathing criteria beyond OSA classification and examining larger cohorts to enable differentiation within the McGill score 1 OSA group.

Chapter 1: Background, Aims and Research Questions

1.1 Background

Restless sleep is a frequently reported symptom, yet it is not routinely defined or reported from a standard paediatric sleep study. It is a common complaint amongst various sleep disorders including obstructive sleep apnoea (OSA), restless leg syndrome (RLS) or can remain as a standalone when other disorders of sleep have been excluded.[1] Body movements are an objective measure of restlessness during sleep. This thesis quantifies restlessness as Movement Index (MI, events/h) and Movement Duration (MD, % of time) using both Sonomat (MAT) and Polysomnography (PSG). It evaluates whether movement burden is a measurable and clinically relevant feature in paediatric sleep assessment and explores its role as an adjunct for OSA. It standardises MI/MD reporting across these two recording modalities, quantifying Sonomat-PSG agreement across event duration thresholds and tests the clinical utility of adding this measure to the McGill score 1 (inconclusive) subgroup to aid screening for OSA.

Existing recording modalities such as PSG with or without video, actigraphy and static charge-sensitive systems use heterogeneous scoring rules and reporting metrics, making cross-study comparison and development of normative reference ranges difficult. Chapter 2 explores in detail the historical context of measuring body movements during sleep using various techniques. The recent publication by the International Restless Legs Syndrome Study Group (IRLSSG) defined large muscle movement rules in an attempt to standardise aspects of PSG movement scoring.[2] PSG is resource-intensive, typically single-night and lab-based, and can disrupt natural sleep. First night effects have been documented in paediatric and adult populations and can disrupt sleep architecture.[3,4]

Chapter 3 outlines the methodology used in this thesis, while further details are provided within the data chapters themselves. The Sonomat is a lead-less mattress overlay (requires no direct contact with the patient) for minimally intrusive, multi-night home recordings, enabling large cohorts to be studied and to obtain (closer to) true normative reference ranges. It has been validated as a reliable and accurate tool for the diagnosis of OSA in both adults and children.[5-7] Its use for quantifying gross body movements remains untested.

Chapter 4 compares Sonomat and PSG scored body movements. Stradling et al used video recording analysis and reported more body movements in children with OSA than in controls, with burden reduced after adenotonsillectomy.[8,9]

Chapter 5 evaluates whether MI and MD from Sonomat and PSG differentiate OSA status and whether movement burden add value to McGill oximetry score, focusing on those with the McGill score 1 (inconclusive) subgroup.

Chapter 6 synthesises the findings, presents the conclusions and proposes directions for future research.

1.2 Aims

Primary Aim: Quantify cross-modality agreement between Sonomat and PSG for gross body movement metrics (MI and MD) using PSG-defined Total Sleep Period (TSP) as denominator (Chapter 4).

Secondary Aim: Compare MI and MD by OSA status and explore the value of adding movement indices to the McGill score of 1 group. (Chapter 5) to aid screening for OSA.

1.3 Pre-specified research questions

1. What is the agreement between Sonomat and PSG movement metrics (MI and MD) for all events (no minimum duration) and for events filtered by individual movement duration thresholds of ≥ 1 s, ≥ 3 s, ≥ 5 s, and ≥ 7 s?
2. How closely do automated Sonomat Scoring methods reproduce manual scoring for MI and MD?
3. To what extent do movement metrics (MI and MD) discriminate OSA status?
4. What incremental value do movement metrics (MI and MD) add within the inconclusive McGill score 1 (inconclusive) subgroup on screening oximetry?

Chapter 2: Understanding Sleep Movements in Children: Assessing Body Movements, Normative Data, Clinical Implications and Future Directions.

This chapter adapts material from: Lu, M., Fitzgerald, D. A., Norman, M. B., Sullivan, C. E., & Waters, K. A. (2025). Paediatric sleep movements: a review of methodologies, normative data, disease associations and research gaps. Journal of Clinical Sleep Medicine, jcsm-11748.
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2.1 Chapter Overview

Restless sleep is a common but rarely quantified metric in paediatric sleep studies. This chapter reviews methods for measuring gross body movements during sleep such as Polysomnography (PSG) with or without videos, actigraphy, static charge-sensitive systems, and contactless devices, with emphasis on inconsistent scoring rules, denominators and reporting. We synthesise normative datasets and highlight how heterogeneity limits cross study comparison. We describe recent IRLSSG large muscle movement criteria and position Movement Index (events/hr) and Movement Duration (%) as the thesis-wide metrics, using PSG-defined Total Sleep Period (TSP), defined by sleep onset to the last epoch of sleep, as the primary denominator. Clinical links to Obstructive Sleep Apnoea (OSA), Restless Leg Syndrome (RLS), Periodic Limb Movements of Sleep (PLMS) and neurocognitive and behavioural outcomes are summarised and key gaps identified. This chapter establishes terminology and motivates the core methods (Chapter 3) that underpin the Sonomat-PSG agreement study (Chapter 4) and clinical analyses (Chapter 5).

2.2 Introduction

Restless sleep is a frequently reported symptom among children, yet objective quantification and clinical interpretation of this disorder remain limited. PSG is the established assessment tool for sleep disorders for people of all ages; however, it lacks standardised metrics to quantify restlessness. While some cases coincide with Obstructive Sleep Apnea (OSA) or movement disorders like PLMS, PSG often fails to explain restless sleep, even while excluding other conditions.

One proposed method for assessing restlessness is quantifying body movements during sleep. While scoring criteria for Periodic Limb Movements (PLM) were introduced in 1993,[10] there was no accompanying guideline for defining large body movement parameters or reporting movement indices until recently. The introduction of consensus criteria by the IRLSSG marks a step toward standardisation ***(Table 1),*** yet widespread adoption and validation remain limited. Furthermore, normative values remain scarce, making it difficult to establish clinical thresholds for intervention or to guide treatment recommendations. Recently, restless sleep disorder (RSD) was proposed as a distinct condition characterised by excessive nocturnal body movements that disrupt sleep, distinguished from other sleep disorders using the definition of a high movement index on video PSG. [11,12]

Table 1: Consensus Diagnostic Criteria for Restless Sleep Disorder (RSD) [12]

1.	A complaint of 'restless sleep' as reported by the patient's parent, caregiver (or bedpartner) or the patient
2.	Restless sleep movements involve large muscle groups of the whole body, all four limbs, arms, legs or head.
3	The movements occur during sleep or when the individual appears to be asleep
4	Video PSG shows a total movement index (by video analysis) of 5 or more per hour of sleep
5	Restless sleep occurs at least three times per week
6	Restless sleep has been present for at least three months
7	Restless sleep causes clinically significant impairment in behavioural, educational, academic, social, occupational, or other important areas of functioning as reported by patient's parent/caregiver/bed partner or by the patient including: a. daytime sleepiness, b. Irritability c. Fatigue d. Mood disturbance e. Impaired concentration f. Impulsivity
8	The condition is not better explained by another sleep disorder, medical disorder, mental disorder, behaviour disorder, environmental factor (e.g. sleep disordered breathing, restless legs syndrome, periodic limb movement disorder, sleep related rhythmic movement disorder, insomnia disorder, atopic dermatitis, seizure disorder or the physiological effects of a substance e.g. caffeine).

PSG: Polysomnography

Early research on sleep movement relied on direct observations,[13-15] photography [16] and simple video analysis.[8,9,17] Over-time, this evolved into PSG-based movement scoring, [18-24] followed by less invasive techniques such as a static charge sensitive bed (SCSB),[25] Sonomat [26] and actigraphy, the latter becoming the most widely used tool for studying sleep-related movements to date.[27-42]

Historically, the importance of body movements during sleep was recognised so that in 1968, Rechtschaffen and Kales (R&K) introduced the electroencephalogram (EEG) artifact method for scoring movement on PSG, [43] a broad framework that persisted for decades. Later novel tools such as the SCSB in the 1980s provided additional ways to measure sleep motility with more granular measurement capacity.[44] More recently, contactless movement sensors, such as the Sonomat, have emerged offering the potential to capture full body movements in a home setting without the intrusiveness of traditional PSG leads. [5] Despite these advancements, methodological inconsistencies remain, making comparisons between studies difficult due to differences in measurement techniques, movement indices, and duration cutoffs (e.g. ≥1 s vs. ≥3 s).

Normative values for sleep-related movements have been published across both adult and paediatric populations, but they use a range of measurement tools and definitions, and include technologies of video, video PSG, SCSB and actigraphy (***Table 2).*** We compare the values provided across different disease entities such as attention deficit hyperactivity Disorder (ADHD), [20,22,23,27] OSA, [8,45] near miss sudden infant death syndrome (SIDS), [46] Apparent Life Threatening Events (ALTE), [31] iron deficiency anaemia (IDA) [47] and narcolepsy. [40]

Table 2: Types of devices used to measure movement, cohort of patients studied, measures used in published results.

Type of Device	Citation	Basic Study information	Paediatric	Adult	Movement duration	Movement index
Photography						
	Dekoninck et al 1992 [16]	Normal; Single night	Yes	Yes	No	Yes
Video recordings						
	Stradling et al 1988 [8]	Normal; OSA; Pre and post Ts and As	Yes		Yes	No
	Stradling et al 1990 [9]	Normal; OSA; Pre and post Ts and As	Yes		Yes	No
	Bader et al 2000 [17]	Normal; Bruxism; Single night		Yes	No	Yes
PSG+/- *Video recordings						
	Busby et al 1981 [20]	Normal; 'Hyperkinetic'; 5 nights	Yes		Yes	No
	Wilde-Frenz et al 1983 [18]	Normal; Single night		Yes	No	Yes
	Coons et al 1985 [46]	Normal; Near miss SIDS';2 time points	Yes		Yes	Yes
	Shimohira et al 1998 [21]	Normal; Single night	Yes		No	Yes
	Konofal et al 2001 [22]	Normal; ADHD; Single night	Yes		Yes	Yes
	Coussens et al 2014 [45]	Normal; OSA; Primary snorer; Pre and post Ts and As	Yes		Yes	Yes
	Stefani et al 2015 [19]	Normal; Single night		Yes	No	Yes
	DelRosso et al 2019 [24]	Normal; RSD; RLS; Single night	Yes		No	Yes
Static Charge Sensitive Bed						
	Erkinjuntti et al 1988 [25]	Normal; 'Neurologically impaired'; 3 time points	Yes		Yes	Yes
	Kronholm et al 1993 [48]	Normal; Single night		Yes	No	Yes
	Sjoholm et al 1992 [49]	Normal; Bruxism; Single night		Yes	Yes	Yes
	Kaartinen et al 2003 [50]	Normal; 14 nights		Yes	Yes	Yes
Actigraphy						
	Porrino et al 1983 [27]	Normal; ADHD; Single night	Yes		No	Yes
	Van hilten et al 1993 [28]	Normal; 6 nights		Yes	Yes	Yes
	Tirosh et al 1993 [29]	Normal; ADHD; 2 nights	Yes		No	Yes

	Sadeh et al 1994 [30]	Normal; 2 nights	Yes	Yes	No	Yes
	Einspieler et al 1994 [31]	Normal; ALTES; Apnoeas; 2 time points	Yes		Yes	Yes
	Aronen et al 2001 [32]	Normal; 3 days	Yes		No	Yes
	Angulo-Kinzler et al2002 [33]	Normal; Iron deficient anemia; 3 time points	Yes		No	Yes
	Scher et al 2004 [34]	Normal; 6 time points	Yes		Yes	No
	Acebo et al 2005 [35]	Normal; 1 week	Yes		No	Yes
	Gaina et al 2005 [36]	Normal; 1 week	Yes		Yes	Yes
	Natale et al 2009 [37]	Normal; Insomnia; Single night		Yes	No	Yes
	Scher et al 2012 [38]	Normal; 3 nights	Yes		Yes	No
	Filardi et al 2015 [39]	Normal; Narcolepsy Type 1; IPH; 7 days		Yes	No	Yes
	Filardi et al 2016 [40]	Normal; Narcolepsy; 7 days	Yes			
	Tonetti et al 2016 [41]	Normal; 3 time points	Yes		No	Yes
	Meltzer et al 2019 [42]	Normal; Single night	Yes		Yes	Yes

***ADHD** – Attention Deficit Hyperactivity Disorder; **ALTE** – Apparent Life-Threatening Event; **IPH** – Idiopathic Hypersomnia; **OSA** – Obstructive Sleep Apnea; **PSG** – Polysomnography; **RLS** – Restless Legs Syndrome; **RSD** – Restless Sleep Disorder; **SIDS** – Sudden Infant Death Syndrome; **Ts and As** – Tonsillectomy and Adenoidectomy.*

Understanding and treating restlessness during sleep involves identifying its underlying pathophysiology, so for comparison treatments are compared for other motor related sleep disorders such as restless leg syndrome (RLS), PLMS and RSD. These treatments include Iron, vitamin D, dopaminergic agonists, and other medications.[51-54]

This review focuses on paediatric populations when examining different methodologies for measuring sleep movements, with the primary objectives being to:

(1) Compile and compare sources of normative data,

(2) Compare movement differences across (associated) disease entities,

(3) Evaluate the consequences of restless sleep,

(4) Identify research gaps and areas for future studies.

2.3 Methods of measuring movements during sleep

The study of body movements during sleep predates the use of EEG in PSG, initially serving as a visual indicator of wakefulness versus sleep. [55,13] Present-day studies assessing sleep interruptions must also carefully evaluate their chosen measurement methods. PSG is the most frequently used method for measuring sleep and sleep-associated disorders but its reliance on multiple contact based leads may itself disrupt sleep quality. [56,57] To address this, contactless alternatives were developed, including the Sonomat, a thin foam sheet embedded with movement sensors that allows for home-based sleep monitoring in a natural environment. Unlike the PSG, the Sonomat does not require wires or probes, making it a less intrusive option for assessing restless sleep disorder based on current consensus criteria.

This review identifies studies that quantitatively measured body movements during sleep in children. ***Table 2*** categorizes these studies according to measurement methodology, specifying whether they included normative cohorts or groups with medical conditions. The focus is on paediatric data, but some studies include adult comparisons. To enhance clarity, data are summarized as providing movement duration or movement indices, rather than listing specific values. More detailed metrics can be found in ***Supplementary table 1***. ***Table 3*** highlights studies that examined movement patterns in various medical conditions, and summarises key findings including sample sizes, key outcomes, and comparisons of movement metrics between affected children and controls. These tables provide a broad overview of current research, acknowledging methodological diversity while offering a structured reference for understanding movement measurement approaches in paediatric sleep studies. More details of studies presenting normative data are included in ***Supplementary Table 1.***

Table 3: Medical conditions, citations, key findings and examples of comparative movement measurements.

Condition	Citations, (N)	Key findings	Example of comparative movement measurements
OSA	Stradling et al 1988 [8] (N = 8)	OSA moved more than controls. Movement improved after Ts and As	Controls = 4.7% (% time moving) Vs OSA = 13.1%
	Stradling et al 1990 [9] (N = 61)	OSA moved more than controls. Movements improved after Ts and As	Controls = 4.6% (% time moving) OSA Pre surgery = 8.75% and OSA Post surgery = 5%
	Coussens et al 2014 [45] (OSA N = 20, PS N = 24)	OSA moved more than primary snorers who moved more than controls	Controls = 2.1% (% time moving) vs PS = 2.1% vs OSA = 2.2% Controls = 9.4/hr (index) vs PS 10.5/hr vs OSA = 16.4/hr
ADHD	Busby et al 1981 [20] (N = 11)	'Hyperkinetic' children moved more than normal controls	Controls = 1.96 minutes vs 'Hyperkinetic' = 3.07 minutes
	Konofal et al 2001 [22] (N = 31)	ADHD moved more than controls.	Controls 6.5% (% time moving) vs ADHD = 12.7% Controls 62.26 (total movements) vs ADHD =90.1
	Porrino et al 1983 [27] (N = 12)	ADHD moved more than controls	Controls 32/hr (index) vs ADHD = 48/hr
Bruxism	Bader et al 2000 [17] (N = 11)	Bruxers moved more than controls.	Controls 18/hr (index) vs Bruxers = 41/hr
	Sjoholm et al 1992 [49] (N = 12)	Bruxers moved more than controls	Controls 55.3sec/hr vs Bruxers 87.4 sec/hr Controls 14/hr (index) vs Bruxers 21.4/hr
Near miss SIDS	Coons et al 1985 [46] (N = 10)	Infants with near miss SIDS moved less than controls	Normal = 5 minutes of movement/minutes of sleep Vs Cases = 3.7 minutes of movement/ minutes of sleep
ALTE	Einspieler et al 1994 [31]	Infants with ALTE moved less than controls at 6 months but not at 2 months	Controls = 4.3/10 min epochs ALTE = 2.44/10 min epochs
Iron deficiency	Angulo-Kinzler et al 2002 [33] N = 17	Iron deficient anaemia infants moved more than controls	Controls 15/min vs cases = 25.1/min* Indices at other age (months) are also reported. **Numbers derived from graph*
RSD, RLS	Delrosso et al 2019 [58] N = 15 RSD and 15 RLS	RSD moved more that RLS and controls	Controls 2.25/hr, vs RSD 7.34/hr vs RLS 3.83/hr
'Neurologically impaired'	Erikinjuntti et al 1988 [59] N = 21	No difference in movement between neurologically impaired infants vs controls	Controls 30/hr vs 34/hr (major movements at 1 week of age) Index for minor movements and other age groups reported
Narcolepsy	Filardi et al 2015 [39]	NT1 moved more than IH and controls	Controls 9.9/min vs IH 16.1/min vs Narcolepsy 29.8/min IH = Idiopathic hypersomnia
	Filardi et al 2016 [40]	NT1 moved more than controls	Controls 11.64/min vs Narcolepsy 30.54/min

ADHD *– Attention Deficit Hyperactivity Disorder;* ***ALTE*** *– Apparent Life-Threatening Event;* ***IH*** *– Idiopathic Hypersomnia;* ***NT1*** *– Narcolepsy Type 1;* ***OSA*** *– Obstructive Sleep Apnea;* ***PS*** *– Primary Snorer;* ***RLS*** *– Restless Legs Syndrome;* ***RSD*** *– Restless Sleep Disorder;* ***SIDS*** *– Sudden Infant Death Syndrome;* ***Ts and As*** *– Tonsillectomy and Adenoidectomy.*

Observation and photography

Early methods for measuring sleep movements relied on direct observation to characterise behavioural and sleep states in infants. [13-15] De Koninck et al. later used photography to analyse sleep positions and position shifts across nights in different age groups. [16]

Although historically valuable, these methods were labour-intensive, prone to data loss if the subject moved out of view, and required room lighting, which could disrupt sleep. With the advancement of more reliable methodologies, their use in sleep movement studies was largely replaced.

Video recording

Stradling (1988) introduced an automatic video-based method that detected sleep movements by analysing light intensity changes on a screen. In a small paediatric cohort (n=16), he demonstrated that OSA disrupts sleep even without oxygen desaturations. [8] A larger follow up case control study confirmed these findings, showing a reduction in movement post adenotonsillectomy, further supporting the link between OSA and sleep fragmentation as measured by movement. [9]

Although video-based methods provide direct movement visualisation they have limitations. Movements beneath bedsheets or subtle peripheral movements may go undetected, and earlier studies require room lighting, which could disrupt sleep. Infrared video technology has since resolved this issue, allowing for unobtrusive nighttime recording.

Polysomnography (PSG) +/- video

PSG is the gold standard for evaluating sleep disordered breathing, capturing EEG, electrooculography (EOG), electromyography (EMG), electrocardiography (ECG) and respiratory data. It was used, with or without video, to assess body movements during sleep, but inconsistent methodologies and scoring criteria over time now make cross study comparisons difficult.

Historically, Rechtschaffen and Kales (1968) (R&K) introduced the EEG artifact method, defining movement time based on epochs where muscle tension obscured more than half of the EEG and electrooculogram (EOG) signal.[43] This method was widely used to quantify movement in both paediatric and adult populations.[18,20,21] Busby et al. applied this rule to compare sleep movements in 'hyperkinetic' vs. normal children, reporting the 'absolute' (total minutes) and relative (% movement time over total sleep time, TST) values. [20] This epoch-based method likely underestimates movement frequency and duration, as shorter duration events that are common in children may go undetected.

Alternative PSG-based methods include:

- Additional epoch-based movement scoring: Wilde-Frenz et al. classified movements as minor and major based on the number of affected PSG channels, [18] whereas, Shimohira et al. refined movement characterisation to differentiate specific body parts. [21]
- Individual movement event scoring: Coussens et al. showed that marking movement based on at least two PSG channels, including EMG, was more sensitive in detecting sleep disturbances in children with OSA when compared to the R&K method. [45]
- Movement duration thresholds: DelRosso et al., further refined movement scoring in children with an RSD using ≥1 s movements, [24] where as other studies evaluate movements ≥ 3 s. [45]
- Despite these limitations, PSG remains the established reference standard for comprehensive sleep assessment, offering standardised acquisition protocols, established normative values across age groups, and simultaneous monitoring of multiple physiological signals including EEG, EMG, EOG, ECG, and respiratory measures. These features continue to support its role as the reference method against which new ambulatory or non-EEG devices are evaluated.

To improve research consistency, the IRLSSG recently proposed standardized scoring of large muscle movements (LMM) in PSG. [60] A comparison of PSG based LMM scoring with video PSG in children with RSD found PSG detected more movements overall, but with similar total movement duration (95.4% of video detected movements were also identified on PSG).[61]

PSG has several limitations in accurately quantifying movement as a measure of restlessness.

- Video-based PSG may miss movements beneath blankets, particularly small peripheral movements.
- Leads and sensors themselves, may induce arousals and affect natural movement patterns. The potential impact of PSG on movement indices remains unproven, as no studies have compared movement indices between PSG and non-PSG nights in normal cohorts.
- First night effects and lab settings may alter sleep behaviours compared to home settings. Actigraphy studies in adults, suggest that sleep is less disturbed in home environments, supporting the idea that PSG in lab conditions may influence movement indices during both sleep and wakefulness. [26]

It is important to emphasize that movement patterns in children differ from those in adults, as children spend less time immobile when awake.[32,62] Further research is needed to understand how different methodologies, environments, and scoring techniques impact movement assessment in children.

Actigraphy

Actigraphy is a non-invasive, cost-effective tool for studying sleep wake patterns based on movement. It uses accelerometers (single or multi-axis) to detect motion and was widely applied in insomnia, circadian rhythm disorders, OSA, and post therapy monitoring. Typically worn on the wrist, ankle or abdomen, it allows for extended home-based monitoring, capturing sleep in a naturalistic setting. Actigraphy is highly sensitive for detecting sleep but has lower specificity for detecting wakefulness after sleep onset. Validation studies have confirmed its reliability in assessing sleep and wake patterns for normal infants, children, and adults. [30,35,63] Night to night stability was demonstrated in both normal and neurologically abnormal infants when sleep is measured over multiple nights. [38,63,64] In children, Sadeh et al. found consistent actigraphy data across disturbed sleepers and normal controls. [64] In adults, actigraphy is unaffected by the first night effect when performed in the home setting. [28]

Despite its advantages, actigraphy has several methodological considerations:

- Underestimation of wakefulness in adults due to motionless wake periods. [65,66]
- Overestimation of wakefulness in young children, who exhibit increased nocturnal movements. [67,68] The wakefulness measurement changes with age, as school age children become less active while awake, influencing calculations that include time asleep as a parameter. [42]

Actigraphy is commonly used to measure sleep movements and normative data across age groups were published (see ***Table 2***). [28,30,32,34-38,40-42,47,69,70] Methodologies and units of measurement have varied across studies:

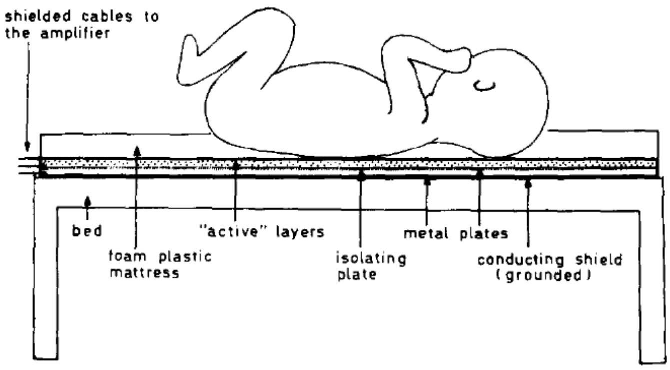
- Activity count per minute is the most consistent metric, facilitating comparisons across studies. [30,35,37,40-42,47]
- Some studies assess activity count over different epoch time frames, [28,32,36] others measure movement duration as a percentage of TST or relative to individual epochs. while others have assessed movement duration as a percentage of TST or in relation to individual epochs. [27,28,34,36,38,42]
- Monitoring duration has also varied, ranging from two days to a week, and longitudinal studies have evaluated multiple time points over several years. (See ***Table 2***)

Actigraphy has several limitations in measuring sleep movements, particularly in detecting full body movement. Since single limb accelerometry only captures motion from the attached site, it may miss movements occurring in other parts of the body. While multi-site actigraphy can improve detection, it’s clinical application remains challenging, especially in the paediatric population. In home settings, artifacts may arise due to factors such as device placement, breathing movements and wrist positioning during sleep. [71]

Static Charge Sensitive Beds (SCSB)

The SCSB consists of two metal plates separated by a wooden insulator and placed beneath a cushioned mattress (See figure 1). As the body moves during sleep, it generates a static charge that spreads across the active layers of the mattress, resulting in a potential difference between the metal plates. [44] Erkinjuntti (1988) used this technology to compare sleep movements in both healthy infants and neurologically impaired infants at 1 week, 1 month, and 3 months of age. [25] While no significant differences in movement frequency were found between groups, both the healthy and neurologically impaired groups showed a natural decline in body movements with increasing age. Kirjavainen et al. later compared short movement detection (<5 s) between PSG and SCSB, finding that PSG significantly underestimated these movements compared to the SCSB, especially in those with OSA and sleep fragmentation. [72] Their study also demonstrated that SCSB characterized rapid eye movement (REM) and non rapid eye movement (NREM) sleep based on respiratory movement patterns, with an average 93.9% (SD 3.6, range 82-98.4%) concordance in sleep wake state recognition compared to PSG. However, SCSB's sensitivity of movement detection declines with age, limiting it's applicability beyond infancy and early childhood. [72]

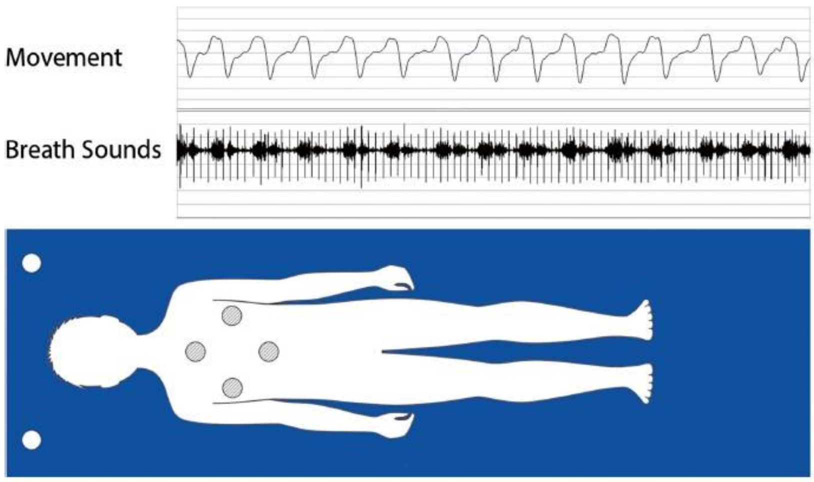
Figure 1. Static Charge Sensitive bed (SCSB) [44]



Sonomat

The Sonomat is a non-invasive, contactless monitoring system like the SCSB but it is designed as a portable mattress overlay ***(Figures 2a & 2b).*** Unlike the SCSB, which detects movements through static charge, the Sonomat uses deformation of the thermoplastic, Polyvinylidene difluoride (PVDF) sensors to detect movement. Although no direct comparisons with PSG or actigraphy exist for movement quantification, validation studies have shown strong agreement between Sonomat and PSG for detecting respiratory events in both adult and paediatric patients. [5,6]

Figure 2a. Photo of the Sonomat on top of a mattress[5] 2b. Signals and Sensor output on the Sonomat[73]

(a) Photo of Sonomat on top of mattress	**(b)** Signals and Sensor output on the Sonomat
	

The Sonomat uses PVDF film sensors, a well-established piezoelectric technology first described in 1969.[75] Its novelty lies not in the sensor material but in the sensor configuration and signal architecture. The device incorporates four distributed PVDF sensors positioned beneath the thorax and abdominal regions. The four-sensor configuration of the mat was designed to maintain signal quality across different sleeping positions and reduce dependence on precise body position relative to a single sensor site, a recognised limitation of single-point systems. [79,80]

The Sonomat records breath sounds, heart sounds and environmental noise during sleep monitoring. It samples movement at 250Hz and the acoustic signals at 4kHz resembling that of a digital stethoscope, extending the range of physiological signals it records. A further distinguishing feature of the Sonomat is that it derives two signal types from the same sensor array: a respiratory movement from thoracoabdominal wall displacement and an acoustic signal that captures snoring and airflow turbulence.[5] The distribution of the four sensors detects movements distributed across the body surface. The portable mattress overlay design, combined with this dual- signal architecture, supports simultaneous assessment of respiratory mechanics and acoustics in home and paediatric settings, where contact-based monitoring may be poorly tolerated.[6,7]

The Sonomat uses continuous recording rather than epoch-based analysis. This avoids the exclusion of brief events that might otherwise fall within PSG epochs scored as wake. Norman et al. found a significant differences in calculated apnoea hypopnea index (AHI) when based on epoch versus continuous scoring of sleep stages. [85]

As a simple, home-based system, the Sonomat supports multi-night recordings in the home environment with minimal patient burden. Norman et al. observed that adults monitored with the Sonomat at home had shorter immobile awake periods and different movement patterns compared to in laboratory PSG recordings, suggesting that home-based recording may reduce first-night effects and capture more representative sleep patterns. [26] Similar differences were observed in movement patterns between home and hospital environments in both term and preterm infants, reinforcing the impact of the sleep setting on movements. [74]

A limitation of the Sonomat is that children may roll off the mattress or leave the bed, potentially affecting data consistency. The ability for multi-night recordings helps mitigate this limitation by allowing for additional assessment. Although the Sonomat was validated for respiratory event detection, its accuracy in quantifying body movements relative to PSG or other measurement tools remains untested. Future research should focus on direct comparisons with PSG and establishing normative movement indices.

2.4 Movements during sleep – what is known and what's normal?

Diagnosing 'restlessness' using motor movements during sleep requires establishing age specific normative values.[42] ***Table 2*** and ***3*** summarise studies that quantitatively measured body movements in paediatric cohorts, reporting either normative data **(*Table 2)*** or comparisons with pathological conditions **(*Table 3)***. More detailed metrics are reported in

Supplementary Table 1. Sample sizes and demographics vary across these studies, which may impact the generalizability of findings.

Numerous studies (***Table 2***) have demonstrated age related changes in the frequency, duration and temporal distribution of movement during sleep. Establishing these normative values is crucial to differentiate between normal variations and pathological conditions that may disrupt sleep.

Age

Multiple studies examining age-related patterns of motor activity during sleep reveal distinct developmental trends. Collectively, they reveal several distinct patterns. Leg movements and PLMS show significant age-related changes in normative values for normal children aged 1-18 years. [86] Several studies report decreasing number(s) of body movements with age, particularly in younger children. [16,25,32,34,35,38,41,42,62,87,88] By contrast, movement levels remain more stable in adults. [19] The decrease in sleep movements is linked to ultradian changes in the proportion of REM sleep and the development of REM motor atonia, reflecting the maturation of the central nervous system. [88-90]

Early in life, ultradian rhythms of motility were observed, echoing similar findings in the foetal state with movements occurring every 75 minutes, predominantly during REM sleep. [91,92] In mild to moderately preterm infants (>30 weeks gestational age), the movement bouts become longer, but the relative time spent in movement remains comparable across all age ranges in infancy. [91] Preterm infants exhibit higher total body movement during sleep than full term infants, [74] and a gradual decline in nocturnal movement is seen in the first months of life. [25,74,93] Infants aged 7 to 11 months exhibit higher motor activity overnight compared to preschoolers and all other older age groups, with peak activity at 10 months. [41] A sharp decrease in nocturnal motor activity occurs between 10-12 months, continuing through 12 and 24 months. Nocturnal motor activity increases again between 30-36 months, before declining once more between 48-60 months of age. [35,38] During the school-age to teenage years (8-17 years), there is a progressive increase in nocturnal motor activity with age. [42] Studies on PLM also demonstrate a peak in limb movements during early adolescence (age 11-13 years). Interestingly, Aronen et al. found that daytime motor activity decreases in school aged children (5-12 years), but nocturnal activity follows a different trajectory. [32] Younger children in the cohort display more consistent movements throughout the night, while older children showed intermittent bursts of movement with less frequency throughout the night. [32] This transition from consistent activity to bouts of activity and inactivity with age was observed in other studies as well. [91] Nocturnal motor activity becomes more stable and consistent between the ages of 10- 60 years. [41]

De Koninck et al. examined position shifts during sleep across different age groups, reporting a decline in frequency with age. Young children (3-5 years of age), shift an average of 4.4 position shifts per hour whereas older adults (65-80 years) shift only 2.1 times per hour. [16] Furthermore, the study found that children show no sleep position preference, while prone sleeping decreases with age, and older adults increasingly prefer right sided sleeping.

Temporal distribution of movements

Spontaneous movements during sleep exhibit a distinct temporal distribution, with variations across sleep stage, age groups and sleep cycles. [62] Studies in both children and adults highlight sleep stage dependent motor activity, with more movements occurring in lighter sleep stages compared to deep sleep.[21,72,94,95]

In toddlers and preschool children, hourly motor activity counts increased over a six-hour period of sleep, with the highest activity in the sixth hour. [41] This trend is more pronounced in infants (7-11 months) than preschoolers (4 years). A similar trend is seen across different age groups, including adults, with peak motor activity between the first and second hour of sleep reflecting the wake to sleep transition. [41] Meltzer et al. confirmed this pattern in children aged 10 years, linking its association with other sleep onset issues commonly described at this age. [42,96] PSG-based studies also showed that movements are more frequent during lighter sleep stages then deep sleep. [21,94,95] Although motor movements are inhibited in adults during REM, [13,97] REM sleep still exhibit more frequent movements than deep sleep. [18,28,95] In young infants (mean age 24 weeks), movements shorter than 10 s occur more frequently in NREM than REM sleep. [72]

Infants and adults exhibit different temporal distribution of spontaneous sleep movements. [62,98,99] Hayes et al. studied healthy premature infants (born 26-36 weeks gestation) and found ultradian rhythms of motility present early in life, resembling foetal movement patterns, where movements occur every 75 minutes, predominantly during REM sleep. [62] In infancy, movement bouts (measure of relative activity and periodicity) are triggered by REM sleep but decline during the first year. [62] They also found that with age, REM-related motor activity becomes less sustained, characterized by shorter bursts of movement alternating with motor atonia, reflecting maturation of inhibitory motor control. [32,62,91] This aligns with studies using phasic mentalis muscle activity to track changes in REM-related motor activity. [100]

In adults, spontaneous sleep movements were linked to EEG-measured K complexes in stage 2 sleep, [98] and transition between slow wave or stage 2 to REM sleep.[99] Stefani et al. established normative values and the topographical distribution of movement in adult healthy sleepers. [19] They found REM movements were shorter and more myocloniform, while NREM movements were more complex, suggesting distinct motor regulation mechanisms between these sleep states. [19]

Studies using actigraphy report consistent movement patterns over multiple nights, [28,64] but Kaartinen et al. found significant inter-subject variation in adult motor activity when measured over 14 nights, [50] suggesting that individual variability may influence movement assessment over extended periods.

<u>Gender</u>

In a large cross sectional study of healthy children and adolescents, Meltzer et al. found that boys had more motor activity and poorer sleep quality. [42] However, this gender difference is inconsistent in the literature. [19,32,36,42,101-104]

In a Video-PSG study of healthy adults, Stefani et al. published normative values of movement index in men (13/hr) compared to women (7.9/hr) after adjusting for age. [19]

2.5 What is known about sleep movements in diseased states?

Table 2 summarises studies comparing sleep-related body movements between various medical conditions and healthy controls. The conditions include ADHD, [20,22,27,105] OSA, [9,45,106] iron deficiency anaemia (IDA), [33] narcolepsy, [40] RSD and RLS, [11,24] bruxism, [17,107] and near miss SIDS/ALTE. [31,46] Most studies report increased sleep-related movements in diseased states compared to controls, except in near-miss SIDS/ALTE, where a reduction in body movements during sleep is observed. [31,46]

While ***Table 2*** provides an overview of the literature, variability in definitions and reporting methods makes direct comparisons challenging. Overall, the collective evidence suggests a link between certain medical conditions and altered sleep-related body movements.

ADHD

Several studies using video-PSG or actigraphy have reported increased body movements during sleep in children with ADHD.[20,22,27,105] Konofal et al. conducted video PSG on 30 unmedicated children (5- 10 years) and found that ADHD children exhibited significantly higher total movement counts (scored by video only), particularly in the upper and lower limbs. [22] The mean total movement duration was almost double in ADHD children compared to controls (55.33 minutes, SD 51.82 vs 27.72 minutes, SD 25.81, p 0.017), with movement duration positively correlating with Conner's questionnaires. [22]

The underlying cause of increased sleep motor activity in ADHD remains unclear but is hypothesized to involve dopaminergic dysfunction. [108] Picchietti et al. found that 64% children with ADHD had PLMS >5/hr, significantly higher than in controls (p<0.0015), [108] potentially contributing to increased total movements. Nakatani et al. further demonstrated higher body movement in REM sleep and shorter resting duration in children with ADHD when compared to controls using video image processing. [105]

Obstructive Sleep Apnoea (OSA) and sleep discorded breathing.

Stradling et al. conducted early studies on sleep movements in children with OSA, [8,9] initially examining a small cohort with enlarged tonsils. They found that children with OSA spent significantly more time moving (13.1% of TST) than controls (4.7%), a difference that normalized post-tonsillectomy (5.9%).[8] In a larger follow up study, pre surgery snoring children moved significantly more (8.75%) than post-surgery (5%) compared to controls (5.1% and 4.6% at matched time points).[9]

Movement arousals are often used to assess sleep fragmentation in children with OSA. [109] Coussens et al. compared movement parameters via video PSG (using PSG channels) in children with OSA, primary snorers, and controls before and after adenotonsillectomy. [45] They found that children with OSA had significantly higher body movements event index (MEI) during TST, NREM and REM sleep when compared to the control group. MEI was also higher in OSA than in primary snorers during REM sleep, though no significant differences were seen between primary snorers and controls. [45] Post surgery, the differences in MEI were no longer observed. [45] While Coussens et al. confirmed increased movement in OSA, their findings differed from Stradling et al. in that they did not find differences in total movement time or mean movement duration.[9,45] Both studies measured movement time as the number of epochs obscured by gross body movements rather than absolute movement duration, which may introduce variability in reported values due to its inherent imprecision.

Additionally, Coussens et al. found that children with OSA exhibited a disrupted sleep structure, characterised by shorter sleep runs when using movement as an indicator of sleep fragmentation. [45] Although adenotonsillectomy eliminated group differences in movement, residual alternations in sleep movement distribution persisted, likely due to mildly elevated obstructive apnoea-hypopnoea index (OAHI) that remained post surgery. [45]

Restless sleep disorder (RSD)

Efforts to better define and evaluate restless sleep in children have gained traction, particularly through the work of DelRosso et al., who proposed a body movement index of 5/hr on video PSG to differentiate RSD from RLS and controls. [24]

Recently, consensus diagnostic criteria were established to formally define RSD,[12] incorporating both subjective reports (day and night) and objective findings from a single night of video PSG (***Table 1).*** In a cohort of 15 school-aged children per group, DelRosso et al. found that children with RSD had significantly higher movement counts and total movement index compared to both RLS and controls. [24] A threshold of 5 movements/hr distinguished RSD with 100% accuracy. A separate study found that PSG alone was more sensitive than video PSG in detecting large body movements, suggesting a higher movement index threshold may be required for RSD diagnosis. [61]

DelRosso et al. also conducted the only prevalence study of this newly defined disorder, reporting that 7.7% of a paediatric sleep cohort referred to a single centre over one year met criteria for RSD in the absence of another sleep disorder. [58] Additionally, RSD frequently coexists with other conditions, such as parasomnias, with nearly one third of patients with NREM parasomnias also meeting criteria for RSD.[110,111] The co-occurrence of NREM parasomnias and RSD was associated with lower sleep efficiency and reduced TST compared to NREM parasomnias alone. [111] These findings suggest that when evaluating parasomnias, PSG assessment for RSD should be considered if the clinical history indicate its presence. [110]

Iron deficiency /anaemia (IDA)

DelRosso et al. identified lower ferritin levels in children with RSD compared to those with RLS (20.8ng/ml SD 8.87 vs 30.3ng/ml SD 12.03, P <0.021). [11] Both met the recommended ferritin threshold for treating RSD, RLS and PLMS, which is 50-75ug/L. [112]

In a prospective case control study, 6 month old infants with IDA exhibited higher motor activity measured by actigraphy compared to non anaemic controls. [47] After iron supplementation, this difference was no longer observed at 12 and 18 months, when IDA had been confirmed as resolved by finger-prick blood sampling. However, at 12 months, ferritin levels in the IDA group (14.3+/-10.2ug/L) remained below the recommended threshold, though improved from baseline (6.15+/-9.2ug/L). Even the non-anaemic controls had ferritin levels below the consensus threshold, with baseline and 12 months levels of 18.4+/-12.8 and 22 +/-13.7 respectively. This study had a small sample size, with higher proportion of male infants, who were shown to have higher activity levels. [19,32,36,42,101-104] Additionally, the actigraphy was placed on the legs, potentially measuring leg movement frequency rather than gross body movements.

Narcolepsy/Idiopathic hypersomnolence

A study of 21 drug naïve children with type 1 narcolepsy revealed increased nocturnal motor activity and decreased daytime motor activity counts compared to sex matched controls, indicating an altered circadian rest rhythm. [40] These findings suggest that actigraphy could be a useful adjunct in the diagnosis of narcolepsy, particularly in cases where there is diagnostic uncertainty. [40] Similar results were initially observed in patients with narcolepsy.[39] The reduction in daytime activity observed in narcolepsy patients may be attributed to a higher daytime melatonin release, peaking between 2-4pm in hypocretin deficient men. [113] The increased nocturnal motor activity further confirmed the well-known sleep fragmentation experienced by individuals with narcolepsy, although the underlying mechanism behind this phenomenon has yet to be fully elucidated.

Sudden Infant Death Syndrome (SIDS)/Apparent life-threatening event (ALTE)

Coons et al. examined the sleep movements in near miss SIDS infants, comparing them to matched controls, using 24 hour polygraphic monitoring at 3 and 6 weeks, and 3, 4.5 and 6 months of age. [46] Near miss SIDS infants exhibited significantly reduced movement during both REM and NREM sleep, along with a lower percentage of movement during TST. The authors suggested this reduction in movement may reflect a failure of the critical arousal response triggered by life threatening apnoeic events. [46] Similarly, Einspieler et al. reported that infants with ALTEs displayed decreased movement at 6 months of age compared to healthy controls, [31] but they did not observe a significant difference in movement at 2 months of age, possibly due to the distinct difference in pathophysiology between near miss SIDS and ALTE, which may explain the discrepancy between findings.

Bruxism

Using combined static sensitive bed and video PSG, Bader et al. found that patients with bruxism have increased short duration (<5 s) body movements during sleep. [17] Similarity, Sjoholm et al. also found an increase in total duration of movements in patients with bruxism, greatest for movements lasting 5-15 s. [49] Bader et al. suggested that the elevated body movements in bruxism supports the hypothesis of a shared central aetiology between bruxism and movement-related sleep disturbances.

Other disorders

Erkinjuntti (1988) used SCSB-based sleep wake cycle scoring to compare sleep related body movements in healthy infants and neurologically impaired infants at various ages (1 week, 1 month and 3 months of age).[25] Movements were categorised in to major (>5 sec), minor (2-5 sec) and twitches (<1 s). While no significant differences in movement frequency were found between groups, both exhibited a decline in movement over time, consistent with age related trends observed in other studies. These findings suggest that neurological impairment in early infancy may not significantly alter gross sleep movement frequency, though data beyond 3 months are limited.
Children with autism exhibit higher level restlessness, as measured by Likert-type scale. [114] No studies to date have compared nocturnal body movements between children with autism against normal controls.
Several other factors with significant and independent associations with nocturnal motor activity include psychological distress, higher fasting blood glucose, electrodermal activity and breathing disturbances. [48]

2.6 What is the impact of restless sleep?

The consequences of restless sleep can be categorised into sleep fragmentation and reduced TST, both of which have significant effects on cognitive, behavioural, and quality-of-life outcomes.

Sleep fragmentation was implicated in daytime sleepiness, cognitive and neurobehavioural dysfunction associated with sleep disorders. [115-119] In children, insufficient sleep, whether due to sleep fragmentation or reduced TST, can manifest as hyperactivity, inattention, impulsivity, poor concentration, disruptive behaviours and poor academic performance. [120] The impact extends beyond childhood, affecting the caregiver's quality of life, as seen in reported improvements after adenotonsillectomy for children with OSA. [121]

Sleep fragmentation can lead to excessive daytime sleepiness, [115] with measurement relying on EEG based arousals or behavioural markers such as movement. [45,115] The arousal index aims to quantify sleep interruptions, and is used when assessing sleep disordered breathing, but its accuracy is limited by poor interobserver agreement. [122] Alternative definitions such as the reappearance of an alpha rhythm in EEG accompanied by an increase in EMG for at least 2 sec, have not significantly improved repeatability. [123]

Adults with OSA show less stable sleep compared to controls, even when the sleep macrostructure remains unchanged. [124] In children with OSA, body movements were used as a marker of sleep fragmentation, given their distinct sleep architecture compared to adults.[45] The quantity and distribution of body movements throughout the sleep period was recognised as a crucial aspect of sleep fragmentation, [45,109,125] with children with OSA showing the shortest sleep runs, normal children the longest and primary snorers falling in between.[45] This indicates an association between sleep continuity and disease severity. Higher AHI values are associated with shorter sleep runs, and even after surgery, children with a history of OSA continue to show significant neurocognitive deficits. [117] Incorporating movement metrics in to sleep studies provides valuable insights into arousal dysfunction and central nervous system regulation.[45,126,127]

Sleep deprivation due to reduced TST has been explored in various studies. Sadeh et al. found that modest sleep restriction (1 hour) in fourth and sixth graders significantly affected memory, attention and visual discrimination [128] Similarly, Touchette et al. showed that a 1 hour sleep reduction in early childhood can be associated with reduced cognitive performance at school entry. [45,129] Early-life sleep reduction has also been linked higher hyperactivity and impulsivity scores, even when sleep duration increases at 3 years of age, though this was based on subjective sleep measures.

2.7 Discussion

A comprehensive overview of the existing literature regarding sleep-related body movements in children, highlights consistencies seen for developmental patterns and variations across medical conditions. While significant progress was made in understanding sleep movement, methodological and clinical challenges remain, requiring further research to enhance diagnostic accuracy and clinical application. ***Table 4*** summarises key areas for future research, outlining priorities for standardisation, technological advancements, large scale studies, and clinical applications.

Table 4: Future directions in Sleep Movement Research

Research Focus	Key Priorities
Standardisation of measurement techniques	- Develop consensus guidelines for best assessment modality, movement indices, duration cutoffs and scoring methodologies - Standardise movement assessment across PSG, actigraphy, and contactless sensors - Conduct comparative studies evaluating non-invasive devices against current standard methodologies.
Integration of advanced technologies	- Machine learning to automate movement scoring and or detection - Expand wearable and under mattress sensors to capture multi-night sleep data in home environment
Large scale and longitudinal studies	- Conduct multi-centre studies with diverse populations, including different ages, sexes and developmental conditions - Validate normative movement indices and diagnostic thresholds for restless sleep disorder, in the home vs laboratory setting.
Clinical applications and outcome based research	- Investigate whether treating conditions like iron deficiency or OSA normalises movement indices and improves daytime functioning - Examine if specific movement patterns (e.g. timing, frequency, distribution) predict neurocognitive and behavioural outcomes

One major limitation in interpreting sleep movement data is the lack of standardised measurement techniques and movement definitions. Studies employ different methodologies, including PSG with manual video scoring, actigraphy and contactless sensors like the Sonomat. Movement indices are reported inconsistently – some use movements per hour, others measure the percentage of sleep time with movement, and some rely on epoch-based scoring. These discrepancies in methodology hinder direct comparisons and likely contribute to the variability seen in normative values. Video PSG may underestimate movements beneath blankets, while actigraphy is limited to detecting movement at the device's attachment site. Likewise, differences in movement duration cut offs (e.g., ≥1 sec vs. ≥3 s) impact reported movement indices with clinical significance, emphasizing the need for standardized measurement protocols**.**

Another challenge lies in sample size and demographic representation. Most studies include only small cohorts and often focus on specific disorders**,** limiting the generalisability of their findings. Additionally, ethnic diversity is poorly captured, as most studies originate from North America and Europe. Expanding research to larger, more diverse cohorts is essential for ensuring broad applicability of movement indices across paediatric populations.

The use of PSG as the primary sleep assessment tool presents another limitation. It's intrusiveness and artificial sleep environment may alter natural movement patterns, compromising its ability to accurately capture sleep-related restlessness**.** Non-invasive movement-monitoring tools, capable of assessing multi-night sleep patterns at home, used across large number of normal cohorts could provide a more ecologically valid representation of paediatric sleep behaviour. Establishing consensus on the most effective methodology for restless sleep is essential for improving research and clinical applications.

Developing non-invasive devices capable of accurately recording sleep movements in a natural setting holds significant promise. While the Sonomat is a mattress overlay with multiple sensors, under-mattress systems use a single sensor area (SCSB);[76] one or two discrete sensors (Emfit-based systems);[77] or load cell sensors mounted at structural points (bed legs).[78] Systems such as wrist actigraphy, record movement only at the limb of attachment for movement detection, and video PSG does not capture movements obscured by blankets. Many other under-mattress systems primarily capture movement-related signals, [76-78,81] while ballistocardiography-based systems focus on cardiac and respiratory mechanics rather than breath-sound analysis. [82-84] It would be beneficial if beyond movement detection, these tools capture sleep-disordered breathing and environmental influences that contribute to restlessness. Comparative studies evaluating their performance against **PSG** are essential to establish their accuracy and clinical relevance. As outlined in ***Table 4***, future research in children should focus on standardising movement assessment methodologies, integrating advanced technologies, expanding large scale studies, and exploring clinical applications to improve the diagnosis and management of restless sleep.

2.8 Supplementary to Chapter 2: Understanding Sleep Movements In Children: Assessing Body Movements, Normative Data, Clinical Implications and Future Directions.

<u>Supplementary Table 1: Summary of sleep movement metrics from articles listed in Table 2.</u>

Article	Normal Cohort (N)	Abnormal Cohort	Explanation of measurements, abbreviations etc.	Movement duration as a % of sleep period	Movement index
Photography					
DeKoninck, J., Lorrain, D., & Gagnon, P. (1992). Sleep positions and position shifts in five age groups: An ontogenetic picture. Sleep, 15, 143–149. [16]	N = 10 in each age group (3-5, 8-12, 18-24, 35-45, 65-80 years)	None	Position Shifts per hour Used photographic analysis (1 frame every 8-9 s).	Not reported	Position shifts per hour <u>Results</u> 3-5 years: 4.4 8-12 years: 4.7 18-24 years: 3.6 35-45 years: 2.7 65-80 years: 2.1
Video recordings					
Stradling JR, Warley A, Thomas G, Belcher R. Analysis of overnight sleep patterns by automatic detection of movement on video recording. J Amb Mon 1988;1:217-22 [106]	N = 8	N = 8 children with OSA (Pre and post - tonsillectomy)	Movements were detected in 12- s epochs	% of epochs registering movements <u>Results</u> C: 4.7 OSA (Pre op): 13.1 OSA (post op): 5.9	Not reported
Stradling, J. R., et al. “Effect of adenotonsillectomy on nocturnal hypoxaemia, sleep disturbance, and symptoms in snoring children.” *The Lancet* 335.8684 (1990): 249-253. [9]	N = 31 Mean age 4.71 years (SD 1.66), Range 2-14 years	N = 61 children with OSA (pre and post T&A)	Movement assessed as % of time moving	% of time moving <u>Results</u> C: 4.6 (2.7-7.8) OSA pre op: 8.75 OSA post op: 5.0	Not reported
Bader G, Kampe T, Tagdae T. Body movement during sleep in subjects with long-standing bruxing behaviour. Int J Prosthodont. 2000 Jul-Aug;13(4):327-33. PMID: 11203650. [130]	N = 8 (non-bruxers) mean age ~ 38 years	N = 11 (bruxism), mean age ~ 38 years	Movements classified by duration: -Class I: <5 s -Class II:5-10s	All movements (% of TST) <u>Results</u> C: 2.3±1 Bruxers: 3.9±1.9	All movements per hour <u>Results</u> C: 18 (SD 11) Bruxers: 41 (SD 23) Class I: C:10±6 Bruxers:26±17 Class II: reported non-significant.

PSG+/- Video recordings					
Busby K, Firestone P, Pivik RT. Sleep patterns in hyperkinetic and normal children. Sleep. 1981 Sep 1;4(4):366-83. [20]	N = 11 boys, aged 8-12 years Over 5 nights	N = 11 hyperkinetic boys	R&K scoring of movement	Movement time (minutes) Results C:1.57-2.23 HK: 2.25 – 3.39	Not reported
Wilde-Frenz J, Schulz H. Rate and distribution of body movements during sleep in humans. Perceptual and motor skills. 1983 Feb;56(1):275-83. [18]	N = 11 (8M, 3F), median age 24 years (21-36yrs)	None	Relative frequency of all movements during sleep = Movements (defined as number of 30 s epochs with movements)/total epochs	Not reported	Relative frequency of all movements during sleep Results Mean 0.15 (0.12-0.2)
Coons, Susan, and Christian Guilleminault. "Motility and arousal in near miss sudden infant death syndrome." *The Journal of paediatrics* 107.5 (1985): 728-732. [46]	N = 10 (3wks), N = 10 (6wks) N= 15 (3mo) N = 10 (4.5mo) N = 10 (6mo)	Near-miss SIDS infants: N = 10 (3wks), N = 7 (6wks), N = 10 (3mo), N = 12 (4.5mo), N = 13 (6mo)	Movement index = number of movements per minute of sleep; movement time = minutes of movement per minutes of sleep movements defined as <15s disruptions of all channels	Percent movement time: Results - 3 wks: C = 5.0%±1.2, SIDS = 3.7% ±1.3 - 6 wks: Control = 5.4% ±1.4, SIDS = 3.5% ±1.7 - 3 mo: Control = 3.2% ±1.0, SIDS = 3.0% ±1.1 - 4.5 mo: Control = 2.0% ±0.69, SIDS = 1.6% ±0.65 - 6 mo: Control =1.4±0.06, SIDS =1.6%±0.07	Movements/min of sleep: Results - 3 wks: Control = 0.17 ±0.07, SIDS = 0.13 ±0.06 - 6 wks: Control = 0.14 ±0.05, SIDS = 0.11 ±0.02 - 3 mo: Control = 0.13 ±0.04, SIDS = 0.13 ±0.03 - 4.5 mo: Control = 0.10 ±0.01, SIDS = 0.10 ±0.05 - 6 mo: Control = 0.10 ±0.04, SIDS = 0.09 ±0.02
Shimohira M, Shiiki T, Sugimoto J, Ohsawa Y, Fukumizu M, Hasegawa T, Iwakawa Y, Nomura Y, Segawa M. Video analysis of gross body movements during sleep. Psychiatry and clinical	N = 5 (children aged 4-12 years)	None	GM1 – Axial rotation GM2 – limb and trunk, no rotation	Not reported	Results Results represented in graph form, refer to article.

neurosciences. 1998 Apr;52(2):176-7. [21]			GM3 – 2 or more limbs, no trunk GM4 – only one limb		
Konofal, Eric, et al. “High levels of nocturnal activity in children with attention-deficit hyperactivity disorder: A video analysis.” *Psychiatry and Clinical Neurosciences* 55.2 (2001): 97-103. [22]	N = 19 (age 5-10y) matched for age and sex	N = 30 boys with ADHD (DSM-IV criteria, medication-free)	Study reported ‘Time spent in motion’ = Total movement duration (min)/Time spent motionless (min) *Derived data reported in this table based on calculations over TST	Total movement duration: Results C: 27.71 ± 25.81 min ADHD: 55.33 ± 51.82 min *Derived movement duration (% of TST) C: 6.5%* ADHD:12.7 %*	Total all movement: Results C: 62.26 ADHD: 90.1 *Derived movement index (total movement/per hour of TST) C: 8.8/hr* ADHD: 12.5/hr*
Coussens, Scott, et al. "Movement distribution: a new measure of sleep fragmentation in children with upper airway obstruction." *Sleep* 37.12 (2014): 2025-2034. [45]	N = 48 (mean age 7.7yrs), 22M; 26F	Primary snorers (PS) N = 24 (mean age 8.4yrs), 13M OSA (pre & post): N = 20 (mean 6.8yrs), 13M	Movement Time (MT) as % of TST Movement Event Index (MEI, events/hr TST): Movement defined by R&K scoring	MT Results C: 2.1% PS: 2.1% OSA: 2.2%	MEI Results C: 9.4/hr PSG: 10.5/hr OSA: 16.4/hr
Stefani A, Gabelia D, Mitterling T, Poewe W, Högl B, Frauscher B. A prospective video-polysomnographic analysis of movements during physiological sleep in 100 healthy sleepers. Sleep. 2015 Sep 1;38(9):1479-87. [19]	N = 100(age 19-77 yrs)	None	Movement index (per hour of TST)	Not reported	Movement index Results Women = 7.9/hr Men 13/hr Median Movement index (per hour): - Total sleep: 10.2/h - NREM: 9.2/h - REM: 14.1/h
DelRosso LM, Jackson CV, Trotter K, Bruni O, Ferri R. Video-polysomnographic characterization of sleep movements in children with restless sleep disorder. Sleep.	N = 15; mean age 10.5yrs	RLS = 15; mean age 9.5yrs	Total movement index (movements per hr of TST)	Not reported	Total movement index Results - C: 2.25 ± 0.63 - RSD: 7.34 ± 1.30

2019 Apr 1;42(4):zsy269. doi: 10.1093/sleep/zsy269. PMID: 30602036. [131]	N = 15; mean age 10.5 y	RSD = 15; mean age 11.9yrs RSD group: N = 15; mean age 9.5 yrs RLS group: N = 15; mean age 11.9 yrs			- RLS: 3.83 ± 1.10
Static charge sensitive bed					
Erkinjuntti M. Body movements during sleep in healthy and neurologically damaged infants. Early Hum Dev. 1988 Mar;16(2-3):283-92. doi: 10.1016/0378-3782(88)90109-0. PMID: 3378532. [25]	N = 16, recorded at 1wk,1mo,3 mo	N = 21 neurological abnormalities (IVH, asphyxia, trauma) recorded at 1wk,1mo,3 mo NI: Neurologically impaired	Major (M): >5s, Minor (m): 2–5s, Twitch (tm): ≤1s Total body movement as % TST	Total body movement ratio (M + m duration as % of TST): <u>Results</u> Controls 1week:14% 1month: 11% 3months: 7% NI 1week:11% 1month: 11% 3months: 7%	Movements/hr during active sleep (AS): <u>Results</u> Major: 1wk,1mo,3mo C: 30, 34, 30 NI:34, 36, 30 Minor: 1wk,1mo,3mo C 24, 14, 17 NI:16, 16, 19 Twitch:1wk,1mo, 3mo C:18, 8, 11 NI:16, 11, 8
Kronholm, Erkki, Erkki Alanen, and Markku T. Hyyppä. "Nocturnal Motor Activity in a Community Sample Erkki Kronholm, Erkki Alanen and Markku T. Hyyppä." *Sleep* 16.6 (1993): 565-571. [132]	N = 199 (age 35-55yrs), Men	None	Nocturnal motor activity (movements/min)	Not reported	Nocturnal motor activity (movements/min) <u>Results</u> 0.302/min (0.067-1.019/min)
Sjöholm TT, Polo OJ, Alihanka JM. Sleep movements in teeth grinders. J Craniomandib Disord. 1992 Summer;6(3):184-91. PMID: 1401136. [107]	N = 12	N = 12 Teeth grinders	Movement duration = time spent moving/hour of sleep period Frequencies of body movements per hour	Movement duration <u>Results</u> TG = 87.4 s/hr C = 55.3 s/hr	Frequencies of body movements per hour <u>Results</u> TG = 21.4 C = 14
Kaartinen J., Kuhlman I., Peura P. Long-term monitoring of movements in bed and their relation to subjective sleep quality. Sleep Hypnosis. 2003;5(3):145-153. [50]	N = 16 healthy adults (8F/8M), mean age 26.2 y	None	Movements classified by duration: - Class A (<5s): small	Mean MT% during TIB: <u>Results</u> 2.2% to 4.3% across 14 nights	Movement frequency per minute (TIB): <u>Results</u> SM: mean 0.16–0.36/min

	14 nights		movements (SM) - Classes B–D (>5s): gross movements (GM) Total movement time (MT%) this was calculated in relation to different periods such as TIB (Time in Bed), FH (first hour in bed), 2-6 (hours 2-6)		GM: mean 0.11–0.21/min
Actigraphy					
Porrino LJ, Rapoport JL, Behar D, Sceery W, Ismond DR, Bunney WE Jr. A naturalistic assessment of the motor activity of hyperactive boys. I. Comparison with normal controls. Arch Gen Psychiatry. 1983 Jun;40(6):681-7. Doi: 10.1001/archpsyc.1983.04390010091012. PMID: 6847335. [27]	N = 12 boys; mean age 8.6 ± 1.9 y 7 days	N = 12 boys with ADHD; mean age 8.6 ± 2.1 y	1 Activity count = 16 movements	Not reported	Activity count <u>Results</u> C: 2 (32 movements)/hr H: 3 (48 movements)/hr
van Hilten, J. J., Braat, E. A. M., van der Vele, E. A., Middlekoop, H. A. M., Kerhof, G. A., & Kamphuisen, H. A. C. (1993). Ambulatory activity monitoring during sleep: An evaluation of internight and intrasubject variability in healthy persons aged 50–98. Sleep, 16, 146–150. [28]	N = 99 healthy adults (aged 50–98 years) 6 nights	None	Movement index (MI) is the % of epochs with any movement (activity count > 0) with respect to all epochs that make up the nocturnal period. Movement detected in 15s epochs	Mean duration of immobility periods (MIP): <u>Results</u> Males: 6.93 ± 3.06 min - Females: 9.76 ± 3.58 min MI (%) Males: 8.69 ± 5.18 Females: 7.04 ± 3.58	Activity count <u>Results</u> 2.7/15 sonds
Tirosh, Emanuel, et al. "Effects of methylphenidate on sleep in children with attention-deficit hyperactivity disorder: an activity monitor study." *American Journal of Diseases of Children* 147.12 (1993): 1313-1315. [29]	N = 20 age- and sex-matched normal controls 7 day	N = 12 children with ADHD (6y 9m–12y 3m)	Activity level = number of zero crossings per night Number of zero crossings per 1 min epochs	Not reported	Activity Level <u>Results</u> Baseline: 9.4 ± 3.0 Methylp Tx: 10.5 ± 2.7 Placebo: 10.1 ± 3.4 C: 9.8 ± 2.7

Sadeh, Avi, M. Sharkey, and Mary A. Carskadon. "Activity-based sleep-wake identification: an empirical test of methodological issues." *Sleep* 17.3 (1994): 201-207. [30]	N = 36 -16 adolescents, 10F/6M, mean age 14.9 ± 0.9 y; -20 adults, 10F/10M, mean age 24.0 ± 2.2 y)	None	Activity recorded in 1 min epochs. Does not define what will generate an activity count.	Not reported	Mean Activity level per minute <u>Results</u> Dominant wrist 6.84 Non dominant wrist 6.16
Einspieler, Christa, et al. "Observation of movements during sleep in ALTE (apparent life threatening event) and apnoeic infants—a pilot study." *Early human development* 40.1 (1994): 39-49. [31]	N = 4 infants 2 at 2 months, 2 at 6 months	ALTE: N = 5 2 infants at 2 & 6 months, 3 at 6 months Apnoeic: N = 5 4 at 2 months, 1 at 6 months	Movement as a % of TST Movement rates/10 minutes Measured general movements, isolated movements in extremities and startles	Movement % Results reporting too heterogenous to summarise Refer to paper	Movement rates/10 min Results reporting too heterogenous to summarise <u>Refer to paper</u>
Aronen ET, Paavonen EJ, Soininen M, Fjällberg M. Associations of age and gender with activity and sleep. Acta Paediatrica. 2001 Feb;90(2):222-4. [32]	N = 66 healthy children; (33 Male/33 Female); age; 5–12.3 yrs 3 nights	None	Mean nocturnal activity (counts per 5-min epoch) average over 3 nights 1-min epoch for analysis of sleep	Not reported	Mean nocturnal activity: <u>Results</u> 93.5 ± 34.4
Angulo-Kinzler RM, Peirano P, Lin E, Algarin C, Garrido M, Lozoff B. Twenty-four-hour motor activity in human infants with and without iron deficiency anemia. Early Hum Dev. 2002 Dec;70(1-2):85-101. doi: 10.1016/s0378-3782(02)00092-0. PMID: 12441207. [47]	N = 18 non-anemic infants, mean age 6 mo	N = 17 infants with iron deficiency anemia (IDA), mean age 6 mo	Movement units/min Leg actigraphy	Not reported	Movement units/min <u>Results</u> Data represented in graph refer to article.
Scher A, Epstein R, Tirosh E. Stability and changes in sleep regulation: A longitudinal study from 3 months to 3 years. International Journal of Behavioural Development. 2004 May;28(3):268-74. [34]	N = 50 (26M/24F), healthy full-term infants followed from 3 to 42 months	None	Data reflect % of activity per minute of sleep	% of activity per minute of sleep <u>Results</u> - 3 mo: 17.8 ± 7.4% - 6 mo: 17.8 ± 6.9% - 9 mo: 17.4 ± 9.2% - 12 mo: 12.5 ± 5.0%	Not reported

				- 20 mo: 11.4 ± 3.9% - 42 mo: 9.3 ± 4.2%	
Acebo C, Sadeh A, Seifer R, Tzischinsky O, Hafer A, Carskadon MA. Sleep/wake patterns derived from activity monitoring and maternal report for healthy 1-to 5-year-old children. Sleep. 2005 Dec 1;28(12):1568-77. [35]	N = 169 (84 boys, 85 girls); age 12–60 months across 7 age groups	None	Mean number of activity counts per minute during sleep period time.	Not reported	Mean activity counts per minute during sleep: <u>Results</u> 12 mo: highest (~exact value not reported but graph shows ~25 counts/min) 24–60 mo: progressively lower (~10–15 counts/min)
Alexandru Gaina, MD, Michikazu Sekine, MD, PhD, Shimako Hamanishi, MHPEd, Xiaoli Chen, MPH, PhD, Sadanobu Kagamimori, MD, PhD, Gender and Temporal Differences in Sleep-Wake Patterns in Japanese Schoolchildren, *Sleep*, Volume 28, Issue 3, March 2005, Pages 337–342 [36]	N = 91 (44 boys, 47 girls); age 13–14yrs 7 nights	None	Movement time (% of sleep period) Total activity score = sum of all activity counts during sleep period Mean activity score = magnitude of activity on a per epoch basis during sleep) epoch length 0.5 minutes	Movement time (% of sleep period) R<u>esults</u> Male Weekday: 13.3% +/- 3.1 Weekend: 14.6% +/- 4.3 Female weekday: 10.1% +/- 2.9 weekend: 11% +/-2.4	Mean activity score during sleep: <u>Results</u> Male Weekday: 16.0 ± 9.4, Weekends: 18.9 ± 14.1, Female Weekday: 9.5 ± 4.7 Weekends: 10.4 ± 5.0
Natale V, Plazzi G, Martoni M. Actigraphy in the assessment of insomnia: a quantitative approach. Sleep. 2009 Jun 1;32(6):767-71. [37]	N = 282 (117M/165F); mean age 38.5yrs (7–65yrs)	N = 126 primary insomnia patients (68M/58F), age 16–71 y (mean 40.4 ± 14.3 y)	Mean motor activity (movements/min): This was calculated for Time in bed rather than TST.	Not reported	Mean motor activity <u>Results</u> C: 10.94 ± 4.53 Insomnia: 16.27 ± 9.51
Scher A. Continuity and change in infants' sleep from 8 to 14 months: a longitudinal actigraphy study. Infant Behaviour and Development. 2012 Dec 1;35(4):870-5. [38]	N = 34 (18M/16F), healthy full-term infants, assessed at 8, 10, 12,	None	Mean percentage of activity per minute of sleep (ACT):	ACT <u>Results</u> 8 mo: 19.66 ± 5.27%	Not reported

	and 14 months			10 mo: 18.79 ± 5.34% 12 mo: 16.17 ± 5.48% 14 mo: 17.20 ± 6.62%	
Filardi, Marco et al. "Actigraphic Assessment of Sleep/wake Behaviour in Central Disorders of Hypersomnolence." Sleep medicine 16.1 (2015): 126–130. Web. [133]	N = 30 (15M/15F); mean age 29 ± 9 y 7 days	NT1: N = 39 (23M/16F); mean age 34 ± 16 y IH: N = 24 (11M/13F); mean age 32 ± 15 y	Number of movements per minute Estimated Sleep Motor Activity (eSMA; movements/min during sleep):	Not reported	Number of movements per minute Results NT1: 29.8+/-14.25 IH: 16.12+/-6.21 C: 9.98 +/- 3.27 Estimated Sleep Motor Activity (eSMA; movements/min during sleep): Results NT1: 29.80 ± 14.25 IH: 16.12 ± 6.21 C: 9.98 ± 3.27
Tonetti L, Scher A, Atun-Einy O, Samuel M, Boreggiani M, Natale V. Actigraphic motor activity during sleep from infancy to adulthood. Chronobiol Int. 2017;34(2):246-253. doi: 10.1080/07420528.2016.1219362. Epub 2016 Aug 30. PMID: 27571845. [41]	Study 1 (Longitudinal): N = 10 (4F/6M), assessed at 7 mo, 11 mo, and 4.7 y Study 2 (Cross-sectional): N = 155, across 8 age groups (10 mo to 60 y)	None	Mean motor activity count (1-min epochs, first 6 hours of sleep):	Not reported	Mean motor activity count Results Study 1 7 mo: 21.15 ± 1.18 11 mo: 18.81 ± 1.98 4.7 y: 10.47 ± 1.10 Study 2 2nd–6th hour: range ~17.47 to 26.76 counts/min
Filardi M, Pizza F, Bruni O, Natale V, Plazzi G. Circadian rest-activity rhythm in paediatric type 1 narcolepsy. Sleep. 2016 Jun 1;39(6):1241-7. [40]	N = 21 (13M/8F), mean age 10.95 ± 2.25 y (range 7–16 y)	NT1: N = 22 (10M/12F), mean age 12.09 ± 2.37 y (range 7–15 y)	Sleep Mean activity count = mean activity counts/min of TIB	Not reported	Sleep Motor Activity Results NT1: 30.54 ± 12.37 C: 11.64 ± 4.18 (
Meltzer LJ, Short M, Booster GD, Gradisar M, Marco CA, Wolfson AR, Carskadon MA. Paediatric motor	N = 671 children and	None	Activity index = (% of sleep or wake epoch in	Activity index Results	Mean activity count (count/min)

activity during sleep as measured by actigraphy. Sleep. 2019 Jan;42(1):zsy196. [42]	adolescents (52% female), mean age 13.5 ± 2.4 y (range 8–17.8 y); US (64%) and Australia (36%)		sleep period with activity > 0 activity value Mean activity count (count/min)	Range: 31.9–42.7% Highest in mid-adolescent boys: 42.7 ± 11.4	Results Range: 4.3–26.3 counts/min across age-sex groups Highest in mid-adolescent boys: 14.3 ± 4.0

ACT – Activity per Minute of Sleep; AS – Active Sleep; C – Control; eSMA – Estimated Sleep Motor Activity; EMG – Electromyography; FH – First Hour in Bed; GM – Gross Motor; HK – Hyperkinetic Kids; MEI – Movement Event Index; Methylp – Methylphenidate; M – Major Movement; MI – Movement Index; MIP – Mean Duration of Immobility Periods; Mo – Months; m – Minor Movement; MT – Movement Time; NI – Neurologically Impaired; PS – Primary Snorer; PSG – Polysomnography; QS – Quiet Sleep; R&K – Rechtschaffen and Kales; SIDS – Sudden Infant Death Syndrome; SM – Small Movements; TIB – Time in Bed; TG – Teeth Grinder; tm – Twitch Movement.

CHAPTER 3: Core Methods and Terminology

3.1 Study Design

The data chapters of this thesis are obtained from a retrospective cohort from a tertiary paediatric sleep laboratory. All participants underwent concurrent overnight polysomnography (PSG, with video/audio) and Sonomat recordings. The analysed sample was a subset of a larger database, restricted to studies with complete raw files and good signal quality on both modalities sufficient for body movement scoring. The selected cohort was chosen to optimise the modality agreement estimates. PSG and Sonomat were scored blindly and independently with no cross-modal curation during scoring.

3.2 Participants

Children aged 2-17 years referred for suspected sleep disordered breathing (SDB). Patients were not screened or selected based on 'restless sleep'.

Inclusion
Patients referred for SDB and availability of high-quality raw signals enabling movement scoring on concurrent PSG and Sonomat.

This selection criterion may introduce a bias towards participants with more stable or higher-quality signals, potentially excluding those with more severe movement artefact or greater movement burden. Recordings excluded due to poor signal quality may differ systematically from those included, and the impact of this selection on the generalisability of the derived movement metrics should be considered. This potential bias is discussed further in the limitations section of Chapter 6.

Exclusion
Patients with primary non respiratory sleep disorders, neurological conditions and requirement for respiratory support were excluded from the study.

3.3 Ethics

The Research was approved by the Sydney children's Hospital Network Human Research Ethics Committee: 2021/ETH00839

3.4 Polysomnography (PSG)

ProFusion PSG5 (version 5.0, Compumedics, Melbourne, Australia) was used to score PSG. Channels include electrocencephalography (EEG; frontal, central and occipital), electro-oculography (EOG), submental and bilateral tibialis anterior electromyography (EMG), electrocardiography (ECG), thoraco-abdominal respiratory inductance plethysmography, nasal flow (pressure transducer and thermistor), snoring (tracheal microphone), pulse oximetry, transcutaneous CO_2, synchronised video and audio, and body position. Sleep stages and respiratory events were scored to American Academy of Sleep Medicine (AASM) using paediatric rules.[134] Absolute (continuous) sleep-epoch scoring using methods defined by Norman et al [85] was applied to define sleep and wake epochs for sub-metrics. Movements were scored based on changes seen on video and or PSG (video/PSG). (See section 3.6).

3.5 Sonomat

The Sonomat (Sonomedical Pty Ltd, Balmain, NSW, Australia) is a device with four embedded thermoplastic fluoropolymer (polyvinylidene difluoride) sensors with a mattress overlay. Each sensor outputs a movement channel sampled at 250Hz and a breath-sound channel sampled at 4kHz. Signals from sensors provide four breath sound channels (Right, Left, Top and Bottom stethoscope) and four movement channels (Right, Left, Top and Bottom Movement). There are two room microphones that record ambient sound at 4kHz and provide two (Right and Left) Room sounds. During the PSG, the Sonomat was placed beneath the bedsheets. Data were viewed in Sonomat Replay V0.0.64.0 software. Respiratory events were scored per established methods.[6] The Sonomat's quiescent-time sleep estimate (Total recording time- movement time) as published previously [5,6] was not used as a denominator in this thesis to avoid circularity for movement analyses.

3.6 Movement definitions and scoring

Movement events were scored independently on video/PSG and Sonomat using the following criteria. An event required detection in 2 channels within the modality. Onset of movement was marked by a ≥ 50% rise from baseline amplitude and offset by a return to baseline.

Video/PSG Movement Channels

- Video
- EEG
- EMG
- Respiratory bands

Movements were scored on video/PSG based on changes seen on Video and or other PSG Channels above.

Sonomat movement channels

- Movement channels
- Sound channels
- Acoustic signals from the stethoscope-equivalent channel were excluded for movement scoring due to non-movement physiological artefact.

Duration threshold and merging rule

All movements were first scored irrespective of duration, then stratified at ≥1 s, ≥ 3 s, ≥ 5 s and ≥ 7 s for analysis. Movements separated by < 1 s were scored as a single event.

Artifact Handling

Episodes attributable to technician handling (e.g. sheet adjustments, sensor repositioning) seen on the video/PSG were retained because such events provide valid like for like comparisons. By design we assumed the same physical movement would be detectable on Sonomat.

3.7 Time bases and denominators

Movement metrics in this thesis are time-based measures that require a defined time window as their denominator. Selecting an appropriate denominator is important for two reasons. First, the PSG and Sonomat systems do not share identical start and stop times; an identical window of time is needed to ensure simultaneously recorded time periods are analysed to make metrics from the two systems directly comparable. Second, the Sonomat records continuously without distinguishing sleep from wake epochs, so it cannot independently define a sleep-based time window.

For these reasons, the primary denominator used throughout this thesis was generated from PSG recordings; Total Sleep Period (TSP). TSP is defined as the interval from the first sleep-epoch to the last sleep containing epoch before the end of the study, as determined by PSG epoch-by-epoch scoring. TSP spans the full overnight window including both consolidated sleep and brief interspersed arousals but it excludes prolonged wakefulness before sleep onset and after the final awakening. The start and end times of the TSP was synchronised to Sonomat recordings and only movement events falling within this PSG-defined TSP were included in the analysis. The time interval of the TSP was applied as the denominator for movement metrics from both, so that Movement Index (MI) and Movement Duration (MD) values from each system are calculated over an identical recording time window and are directly comparable.

PSG-specific sub-denominators: TST and TWT

For analyses using PSG data alone, two additional sub-denominators were derived from PSG epoch-by-epoch scoring. Total Sleep Time (TST) is the sum of all epochs scored as sleep within TSP. TST excludes all wake epochs and is used for sleep-only movement metrics. For example, the MI is restricted to confirmed sleep periods. Total wake Time (TWT) is the sum of all wake-scored epochs within TSP, and is used for movement metrics during wakefulness.

These PSG-specific sub-denominators were applied in analyses examining the clinical utility of movement metrics, for example, comparisons by OSA severity (Chapter 4) where distinguishing movement during confirmed sleep from movement during brief arousals is clinically meaningful. These were not used to compare any Sonomat-derived metrics, since the Sonomat cannot independently determine sleep state. The denominator used for each specific analysis is noted in the relevant chapter methods sections.

3.8 Movement parameters

- Movement Index (MI): number of movement events per hour of the chosen duration (events/hr)
- Movement Duration (MD): cumulative time spent in movement as a percentage of the chosen duration (%) or expressed as total minutes.
- PSG only sub-metrics
    - $MI_{sleep\text{-}only}$ and $MD_{sleep\text{-}only}$ – denominator TST or $MD_{sleep\text{-}only}$ expressed in total minutes
    - MIwake and MDwake – denominator TWT, or MDwake expressed in total minutes
- Mean or median individual movement duration during sleep and during wake

3.9 Respiratory parameters and OSA definition

Apnoea-hypopnoea index (AHI) and mixed-obstructive AHI (MOAHI) were scored to AASM paediatric rules using TST as denominator. OSA was defined as MOAHI ≥1/h and no OSA as MOAHI <1/hr. Oxygen saturation nadir and spontaneous arousal index (EEG arousals not linked to respiratory or leg movements per hour of sleep) were also recorded.

3.10 Oximetry sub-classification (McGill Score)

Overnight oximetry was classified using the McGill score. Scores between 2-4 often indicate OSA. The analysis prespecified a focus on score of 1 (inconclusive group) to test whether movement metrics identified OSA within this subgroup. Within McGill 1, children were stratified by MOAHI (<1 vs ≥1/h) for comparison of movement parameters.

3.11 Data handling and synchronisation

All scored events were exported from video/PSG and Sonomat software as delimited text files containing epoch number, event label, start time and event duration. Device clocks were synchronised and any events with temporal overlap between PSG and Sonomat were treated as a match in movement. Matching was computed bidirectionally: Sonomat to PSG and PSG to Sonomat. Only events occurring within the PSG-defined TSP were included. Basic calculations were performed in Microsoft excel.

3.12 Statistical analysis

Statistical and graphical analyses were performed using Jamovi (version 2.7.40) and GraphPad Prism (version 10.6.1 for macOS, GraphPad Software, Boston, Massachusetts USA). Continuous data are summarised as mean ± SD if the data distribution was approximately normal, otherwise median (IQR). Wilcoxon signed-rank was used for paired data and Mann-Whitney U was used for unpaired data. Associations were assessed with Spearman's rank test. Agreement between modalities were visualised with Bland-Altman plots and comparison by box plots. A P value of 0.05 is considered significant. The primary endpoint is MI with no duration threshold applied and the secondary endpoint is MD with no duration threshold. All other duration thresholds (≥ 1, ≥3 s ≥5, ≥ 7s), PSG-only sub-metrics, and correlations are exploratory with no multiplicity adjustment.

3.13 Quality control and automation

Concordance between Sonomat scoring methods was assessed by inter-rater agreement (event-level matching) and intraclass correlation coefficient (ICC) for MI and MD. Three Sonomat scoring methods were compared: manual scoring (MAT), the built-in automated algorithm (Sonoauto) and a custom rules-based algorithm (Rulesauto) that used a 120 second moving Root Mean Square (RMS) to define a dynamic baseline and detected movement when signal power exceeded 6dB above baseline, with event end at return to below threshold. Both automated outputs were compared against manual scoring on Sonomat and video/PSG.

3.14 Deviations by Chapter

Each results chapter describes specific methods in detail and details any procedural deviations from the core methods above, citing specific duration thresholds, denominators, or scoring variants applied.

Chapter 4: Measuring Nocturnal Body Movements in Children: Sonomat Versus Polysomnography.

This chapter is based on a submitted manuscript currently under peer review. Journal name withheld until the publication decision is notified.

4.1 Chapter Overview

This chapter compares outcomes for quantifying paediatric gross body movements during sleep measured with the Sonomat against those from PSG with video (video/PSG). Movement index (events/hr) and Movement Duration (%) are computed on the PSG-defined Total Sleep Period (TSP). The pre-specified endpoints are cross modality agreement for MI (no duration threshold) and MD (no duration threshold). Duration of movements were filtered at ≥1, ≥3, ≥5, ≥7 s and analysed for sensitivity. Agreement is assessed by Bland-Altman and proportional bias testing, with bidirectional event matching and automation reliability. This chapter provides details of how the Sonomat can serve as a practical comparator for movement burden measurement in a cohort of children referred for suspected sleep-disordered breathing.

4.2 Introduction

Restless sleep is a frequently reported symptom among children.[135] Polysomnography currently serves as the established assessment tool for sleep disorders. Nevertheless, standard reporting metrics often fail to quantify "restlessness," leaving it unexplained even after ruling out other sleep disorders. Measuring body movements during sleep has been suggested as an approach to assess restlessness. Only recently have researchers attempted to reach a consensus in scoring large body movements [60] and establish standardized cut-off values to inform clinical recommendations.[11,61] Despite this, considering the inherent intrusiveness of PSG, which may itself disrupt sleep, it raises the question: is PSG truly the most accurate measure of restlessness? This highlights the ongoing need for methodologies that can more effectively measure restless sleep.

The evaluation of body movements during sleep has evolved from early techniques such as direct observation[74], photography[16], and video[31], to PSG[18-22,24,45,46,136,137] and less invasive methods like actigraphy[27-34,39-42] and static charge-sensitive beds.[25,48-50] Each method poses unique challenges, including difficulty detecting movements beneath bedcovers, reliance on artificial sleep environments, and limited feasibility for capturing night-to-night variability. In addition, measuring sleep-related movements is hindered by inconsistent definitions, varied reporting parameters, and a lack of comprehensive normative data across age groups. To address these limitations, the Sonomat (Sonomedical Pty Ltd, Balmain, NSW Australia), a leadless mattress monitoring system, offers a promising alternative. Unlike traditional PSG, it enables assessment in a child's natural sleep environment while capturing body movements as a proxy for restlessness. Although the Sonomat has been validated for diagnosing sleep-disordered breathing in both paediatric and adult populations,[5,6] its utility for evaluating body movements has not yet been investigated.

Recent advancements in the evaluation of restless sleep have been driven by two important developments. First, DelRosso et al provided video-polysomnographic (vPSG) characterisation of sleep movements (measured by video only) in children diagnosed with restless sleep disorder.[24] Second, in 2021, the International Restless Legs Syndrome Study Group (IRLSSG) published standardized scoring criteria for large muscle group movements during sleep, prompting greater consistency in PSG-based assessments. [60] These advancements highlight the growing recognition of movement analysis as an essential component in both clinical practice and sleep research.

This study extends the field by exploring sleep-related movement data using concurrent Sonomat and video/PSG (PSG plus video for scoring body movements) recordings from children assessed for sleep-disordered breathing. It investigates the potential of the Sonomat to detect and quantify sleep movements. This approach offers an opportunity to evaluate alternative methodologies that may better capture movement-related restlessness beyond traditional PSG frameworks.

4.3 Methods

This retrospective study analysed data from children who underwent concurrent Sonomat and PSG recordings with video.[6] A subset of studies from a larger database was used, limited to those where raw data were accessible and of sufficient quality for scoring. Due to a change in software over time, not all previously recorded studies were retrievable. In addition, only those with high-quality Sonomat data were included in the analysis. The cohort consisted of children with snoring and a clinical suspicion of sleep-disordered breathing. Participants were not specifically screened or selected based on symptoms of restless sleep. The study was approved by the Sydney Children's Hospital Network Human Research Ethics Committee 2021/ETH00839.

Polysomnography (video/PSG)

Polysomnography (including video) data were collected using the ProFusion PSG5 (version 5.0, Compumedics, Melbourne, Australia), which included recordings of EEG (two frontal, two central, two occipital channels), electrooculogram (EOG), electromyogram (EMG) of the submentalis muscle, bilateral anterior tibialis EMG, respiratory signals, oximetry, transcutaneous carbon dioxide ($TcCO_2$), single-lead electrocardiogram, and synchronized video and audio. Sleep stages were scored by expert sleep physicians according to standard American Academy of Sleep Medicine (AASM) criteria[134] and absolute (continuous) sleep epoch scoring.[85] All other sleep parameters were scored using standard AASM criteria.[134]

Movements on the video/PSG were scored (based on video and or changes on PSG channels) according to the criteria outlined (see ***Table 1***).

Signal Channel Criteria: A movement was defined by a change detected in at least two of the following signal channels:

(i) **Video** – any observable movement captured on video.

(ii) **EEG** – a change in the baseline EEG pattern indicating the start of movement, with a return to baseline marking its end.

(iii) **EMG** – a deviation of at least 50% from the baseline amplitude marks movement onset; return to baseline defines the offset.

(iv) **Respiratory Bands** – a deviation of at least 50% from the baseline amplitude marks movement onset; return to baseline defines the offset.

Individual Movement Duration Criteria:

(i) All individual movements were initially scored regardless of duration, then stratified into thresholds ≥1 s, ≥3 s, ≥5 s, and ≥7 s for subsequent analysis.

(ii) There was no upper limit imposed on movement duration.

(iii) Movements occurring within one second of each other were considered part of the same movement event.

The Sonomat

The Sonomat system (Sonomedical Pty Ltd, Balmain, NSW, Australia) is a contactless, pressure-sensitive mattress overlay designed to detect physiological signals during sleep. It contains four identical embedded sensors and two ambient sound microphones. The embedded sensors are made of a thermoplastic fluoropolymer (Polyvinylidene difluoride), which deforms in response to pressure changes and generates electrical signals. Each sensor produces two types of outputs: a movement signal sampled at 250 Hz and a breath sound signal sampled at 4 kHz, comparable to digital stethoscope recordings. There is a total of four (top, bottom, left and right) channels for detecting both movement and sound signals. The room microphones capture environmental sound at the same 4 kHz sampling rate, allowing for contextual analysis of ambient noise. There are two room sound level channels derived from the room microphones.

Movements were scored on the Sonomat based on the following criteria (see ***Table 1***).

Signal Channel Criteria: A movement event required a signal change in at least two channels overall, with at least one of these channels required to be a movement sensor channel. Thus, changes confined to the room sound channels alone were not scored as movement events. of the following eight signal channels:

(i) **Movement channels** (Top, bottom, left and right) – movement onset was marked by a greater than 50% increase in signal activity from baseline, with return to baseline indicating the end of movement.

(ii) **Room Sound channels** (Top, bottom, left and right) – movement onset was defined by a greater than 50% increase in signal amplitude in the room sound channels, with a return to baseline marking the end of the movement.

Individual Movement Duration Criteria:

· All movements were initially scored regardless of duration and subsequently stratified using cut-off thresholds of ≥1 s, ≥3 s, ≥5 s, and ≥7 s for analysis.

· Movements occurring less than 1 second apart were considered part of a single movement event.

Acoustic signals derived from the stethoscope channel were excluded from movement scoring due to their vulnerability to artifacts caused by non-respiratory physiological activity, such as cardiac sounds and gastrointestinal noise.

To reduce misclassification of ambient environmental sounds as body movements, at least one of the two channels required for scoring had to be a movement sensor channel.

***Table 1:* Movement Scoring Criteria video/PSG and Sonomat**

	Video/PSG	SONOMAT
Number of leads	Combination of at least 2 signal channels including - Video - EEG - EMG - Respiratory bands	Combination of at least 2 channels overall, with at least one of these channels required to be a movement sensor channel. - Move (Top, Bottom, Left, Right) - Sound level (Top, Bottom, Left, Right)
Movement duration	Score movements of any duration and filter with thresholds 1, 3, 5 and 7 s	Score movements of any duration and filter with thresholds 1, 3, 5 and 7 s
Movement threshold/start	Movement onset was marked by a greater than 50% increase in signal activity from baseline.	Movement onset was marked by a greater than 50% increase in signal activity from baseline.
Movement end	Movement offset when signal return to baseline indicating the end of movement. Scored as one movement if change in signal is less than 1 second apart	Movement offset when signal return to baseline indicating the end of movement. Scored as one movement if change in signal is less than 1 second apart

(PSG: Polysomnography; EGG: Electroencephalography; EMG: Electromyography)

Signal acquisition parameters for both recording systems are summarised in Table 2. The ProFusion PSG5 amplifier (Compumedics) acquired standard polysomnographic channels, with channel-specific filter settings applied in accordance with American Academy of Sleep Medicine technical specifications. The Sonomat recorded movement signals at 250Hz and acoustic (breath sound) signals at 4000 Hz per sensor, with two additional room microphone channels also sampled at 4000Hz. Sonomat sensors were unfiltered to maximise sensitivity to signal change. Gain and amplification were adjusted individually for each signal.

<u>Table 2:</u> Signal acquisition parameters for PSG and Sonomat.

Signal Type	Channels	Sampling Rate (Hz)	High-pass filter (Hz)	Low-pass filter (Hz)
PSG Compumedics ProFusion PSG5 (version 5.0, Compumedics, Melbourne, Australia				
EEG	6 ch (F3, F4, C3, C4, O1, O2)	256	0.3	35
EOG	2 ch (Left, Right)	256	0.3	35
EMG – submentalis	1 ch	256	10	100
EMG – abdomen, diaphragm	2 ch	256	10	100
EMG – tibialis	1 ch	256	10	100
ECG	1 ch	256	0.3	70
Respiratory Inductance Plethysmography	2 ch (thorax, abdomen)	64	0.1	15
Nasal airflow/pressure	1 ch	64	0.03	100
Sonomat (Sonomedical Pty Ltd, Balmain, NSW, Australia)				
Movement	4 ch (top, bottom, left, right)	250	1.0	100
Breath sounds	4 ch (top, bottom, left, right)	4000	60.0	2000
Room ambient sound	2 ch (Right & left room microphones)	4000	60.0	2000

Abbreviations: ch = channel; EEG = electroencephalogram; ECG = electrocardiogram; EMG = electromyogram; EOG = electrooculogram; HP = high-pass; LP = low-pass;Hz = Hertz

4.4 Data Analysis

Movements were scored independently on both the Sonomat and the video/PSG as a continuous recording in both cases (no epochs). All scored events were exported from the two scoring programs as text delimited files and processed in the same manner using Microsoft Excel (Microsoft, Redmond, WA). The exported files contained epoch number, event name, start time and duration of event. The time recordings from both devices were synchronized to enable accurate comparison. Total sleep period (TSP) was determined from the PSG as defined by sleep onset to the last epoch of sleep. Only events occurring within the TSP were included in the analysis. Calculations were basic mathematical operations.

Movement index and total movement duration were calculated. The movement index was defined as the number of movements per hour within the TSP and the total movement duration was expressed as a percentage of the TSP.

The degree of agreement between the devices was assessed by identifying overlapping movements between Sonomat and video/PSG. Any temporal overlap was considered a match. Matching was calculated bidirectionally: (1) Sonomat detected movements that coincided with those recorded on video/PSG, and (2) video/PSG detected movements that coincided with Sonomat-detected events. In addition, correlations between the two devices were analysed for both movement index and total movement duration.

Movement scoring on the Sonomat (MAT) was evaluated using three methods; manual scoring, the built in automated algorithm (Sonoauto), and a custom rules-based algorithm (Rulesauto) developed to mimic the previously mentioned manual criteria. The Rulesauto method calculated a dynamic baseline using a 120 second moving Root Mean Square (RMS) of the signal. A movement was detected when the signal power rose above 6dB (double the baseline), and the event ended when the signal returned below this threshold. Both algorithm outputs were validated against manual scoring on the MAT and the video/PSG.

4.5 Statistical Analysis

Statistical and graphical analyses were performed using Jamovi (version 2.7.40) and GraphPad Prism (version 10.6.1 for macOS, GraphPad Software, Boston, Massachusetts USA). The Wilcoxon signed rank test was used for paired data (MI and MD by video/PSG and MAT scoring). Spearman's rank correlation coefficient was used to evaluate the strength and direction of the association between movement index and total movement duration as measured by video/PSG and the Sonomat. A significance level of $p < 0.05$ was used. Boxplots and Bland-Altman plots were performed as visual representations of agreement between modalities. The primary endpoint is the MI with no duration threshold applied and the secondary endpoint is the MD with no duration threshold. Sensitivity analyses were applied at other event durations (≥ 1 s, ≥3 s, ≥5 s, ≥ 7s).

Movement index and movement duration was measured repeatedly within each child under four scoring methods (video/PSG, MAT, Sonoauto, Rulesauto) and for three time thresholds (≥ 1s, ≥3s and ≥5 s), giving 12 repeated observations per child (36 children; 432 observations each for MI and MD). Linear mixed-effects models were fitted for MI and MD as the outcome variable and scoring method, Time (duration) threshold and their two-way interaction as fixed effects. A random intercept for subject was included to account for within-subject correlation of repeated measurements. Residual diagnostics were inspected for normality and constant variance and where assumptions were violated, outcomes were $\log_{10}$-transformed.[138] When the Omnibus F-test was significant, we performed pairwise comparisons of estimated marginal means with Bonferroni adjustment for multiple testing.

The inter-rater agreement (IRA) and Intraclass Correlation Coefficient (ICC) were calculated to assess concordance between scoring methods on the Sonomat: manual scoring (MAT), Sonoauto and Rulesauto. The IRA was calculated as the proportion of individual body movement events that were simultaneously identified by both scoring methods and therefore reflects event-level matching between the two. ICC was used to assess the between subject consistency of the summary metrics (MI and MD) derived from each method.

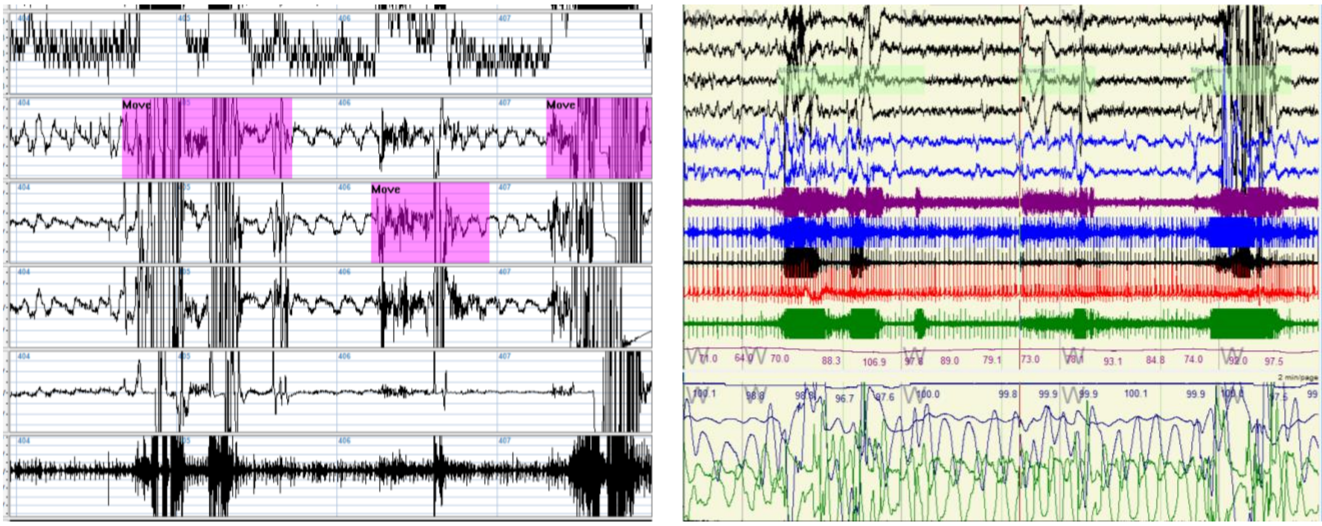
4.6 Results

The study included 36 participants, with a median age of 5.9 years (IQR 3.0, range: 2–12 years). Of the participants, 15 were female and 21 were male.

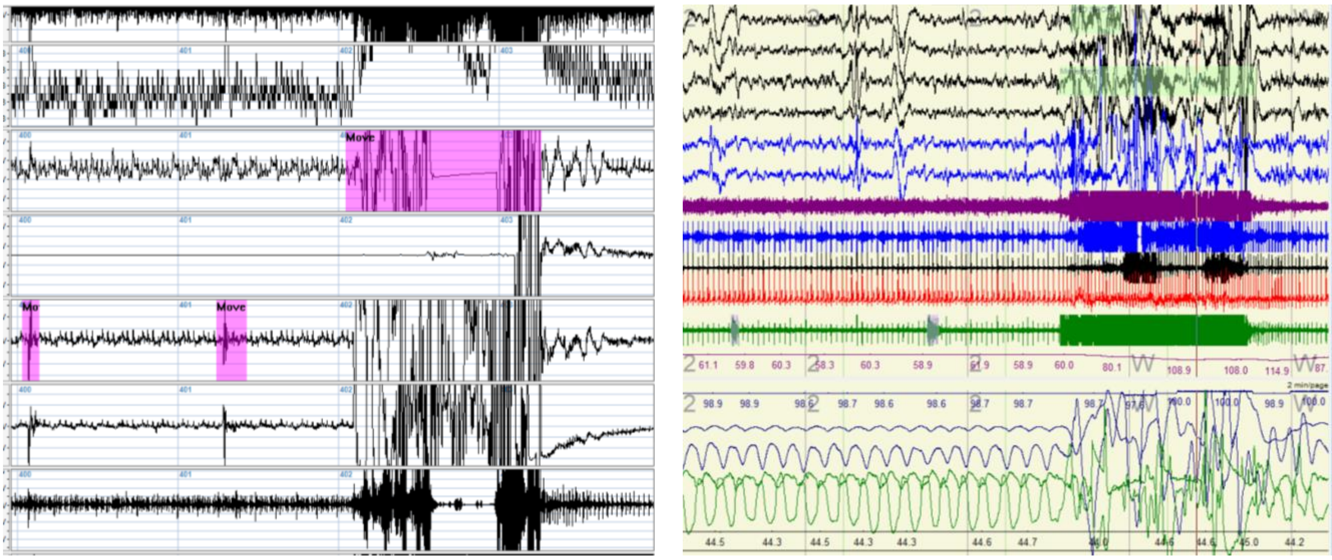
The mean sleep period for participants was 490 minutes (SD 56, range: 333-588 minutes). A total of 7023 movement events were scored on the video/PSG and 11476 on the Sonomat when no movement duration threshold was applied. An example of the corresponding movements between the Sonomat and video/PSG can be seen in ***Figure 1 a&b***.

Figure 1 (a) & (b) Body movements identified simultaneously on Sonomat

(a) Corresponding Sonomat and video/PSG demonstrating 3 body movements



(b) Corresponding Sonomat and video/PSG demonstrating 2 single short movements before a larger body movement



1. Movement Index (MI)

For movements of all durations, the median values for MI were 36.9/hr for Sonomat (MAT) and 20.6/hr for video/PSG (***Figure 2a***), with a median paired difference (MAT-video/PSG) of 14.1/hr (Wilcoxon signed-rank W = 625; $p < 0.001$). Bland-Altman analysis of MI (MAT-video/PSG) showed a mean bias of 15.6, with 95% limits of agreement from -6.9 to 38.0 (***Figure 2b)*** . The median paired difference in MI reduced as the thresholds for marking individual movements increased (≥ 1, ≥3, ≥5 and ≥7 s) see ***Table 3.*** At movements ≥7 s, the median paired difference was no longer statistically significant (median paired difference 0.4, Wilcoxon signed-rank W = 403; p= 0.15). See ***Figure 3a and Table 3.*** Box plots and Bland-Altman plots for movement index at other thresholds (1,3,5 and 7 s) are detailed in the supplementary document (Supp Figure 1).

Figure 2 Movement Index, All movements ***(a)*** Box plot for MI video/PSG Vs MAT ***(b)*** Bland-Altman plot Movement duration (MAT-PSG).

(a) (b)

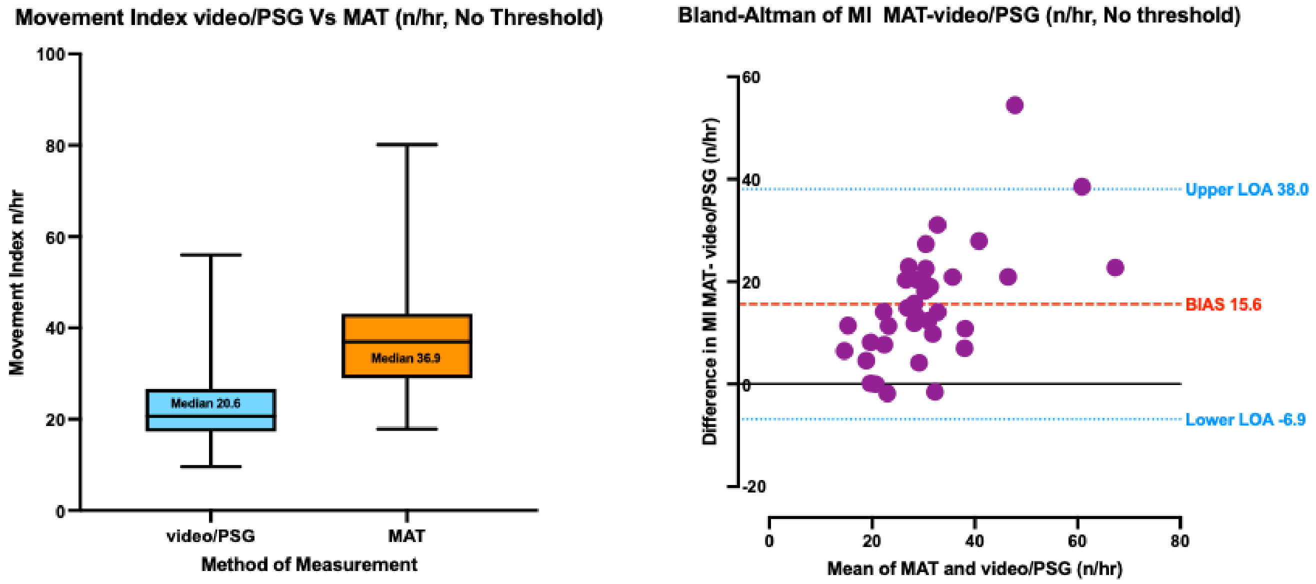
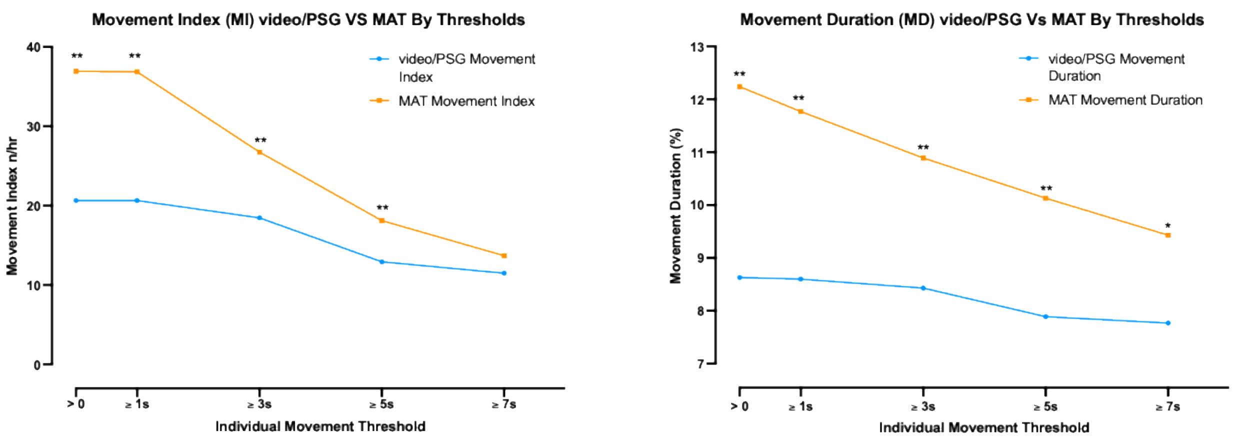


Table 3: Movement Index by movement thresholds; median of paired differences in MI (MAT-video/PSG) and p value.

MI by thresholds	MI Median of Differences (MAT– video/PSG) n/hr	P value (Wilcoxon signed rank test)
Movements no threshold = M0	14.1	<0.001
Movement ≥ 1 s = M1	13.8	<0.001
Movement ≥ 3 s = M3	5.8	<0.001
Movement ≥ 5 s = M5	4.5	<0.001
Movement ≥ 7 s = M7	0.4	0.15

Figure 3 (a) MI by movement thresholds of ≥ 1,3,5 and 7 s (b) MD by movement thresholds of ≥ 1,3,5 and 7 s



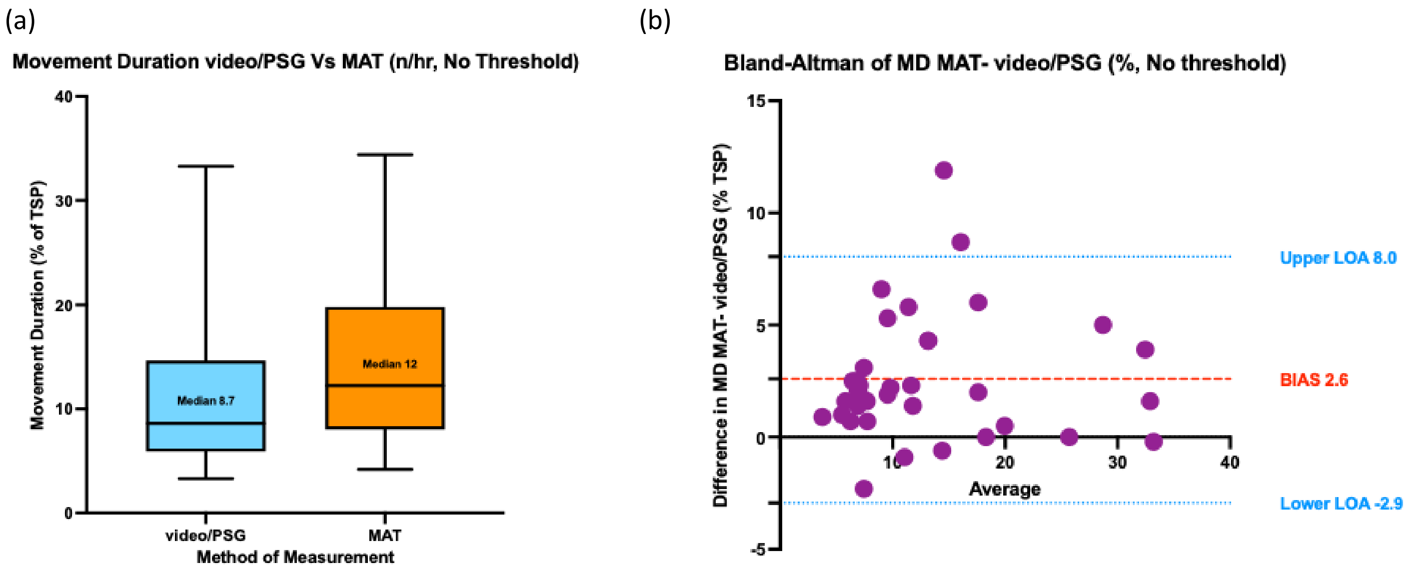
** p<0.01

* p<0.05

2. Movement Duration (MD)

For all movements, the median value of MD as a percentage of TSP was 12% for MAT and 8.7% for video/PSG (***Figure 4 a)***, with a median paired difference of 2.0% (Wilcoxon signed-rank W= 595, p < 0.001). Bland-Altman analysis of MD (MAT-PSG) showed a mean bias of 2.6, with 95% limits of agreement from -2.9 to 8.0 (***Figure 4b)*** . Box plots and Bland-Altman plots of movement duration at other thresholds (1,3,5 and 7 s) are detailed in the supplementary document (***Supplementary Figure 2***).

Figure 4: Movement Duration, All movements ***(a)*** Box plot for MD video/PSG Vs MAT ***(b)*** Bland-Altman plot MD (MAT-video/PSG).



Sensitivity analysis revealed that for movements at all duration thresholds the difference remain significant. See ***Table 4*** and ***Figure 3b***

Table 4: Movement Duration by thresholds; median of paired differences in MD (MAT-video/PSG) and p value.

MD by thresholds	MD Median of Differences (MAT-video/PSG) % of sleep period	P value (Wilcoxon signed rank test)
Movement no threshold = MD0	2.0	<0.001
Movement ≥ 1 s = MD1	2.0	<0.001
Movement ≥ 3 s = MD3	1.6	<0.001
Movement ≥ 5 s = MD5	1.4	<0.001
Movement ≥ 7 s = MD7	0.9	0.01

3. Movement Matching

For all movements MAT identified 88% (IQR 16, 64-99) of movements seen on video/PSG, while video/PSG identified 49% (IQR 15, 24-90) of movements detected by MAT. Matching of movements increased with increased thresholds for individual movement events. See ***Table 5***.

Table 5: Threshold-dependent Matching of Individual Movements between MAT and video/PSG.

Duration class	**MAT matched video/PSG Median** (IQR, Range)	**Video/PSG matched MAT** Median (IQR, Range)
Threshold 0	88 (16, 64-99)	49 (15, 24-90)
Threshold 1	88 (16, 64-99)	50 (18, 24-90)
Threshold 3	88 (12, 66-99)	64 (21, 36-92)
Threshold 5	91 (7.9, 71-99)	68 (21, 37-87)
Threshold 7	85 (11, 65-98)	79 (22, 48-98)

Movements shared by both systems accounted for almost all video/PSG movement time (median of 97% at no threshold, 94% at threshold 7) and for 85-92% of total MAT movement time. See ***Table 6.***

Table 6: Threshold-dependent movement duration for matched movements between MAT and video/PSG.

Duration class	**MAT movement-time also detected on video/PSG (% of MAT total movement time*)** Median (IQR, Range)	**Video/PSG Movement-time also detected on MAT (% of PSG Total movement time*)** Median (IQR, Range)
Threshold 0	85 (16, 66-98)	97 (5.7, 85-100)
Threshold 1	85 (14, 66-98)	97 (5.7, 85-100)
Threshold 3	88 (15, 67-98)	96 (5.4, 83-100)
Threshold 5	88 (15, 68-97)	96 (5.6, 84-99)
Threshold 7	92 (11, 68-99)	94 (5.4, 82-99)

**Percentages are calculated using only movement detected by both systems.*

4. Correlation between MAT and video/PSG – MI and MD

(a) *MI*

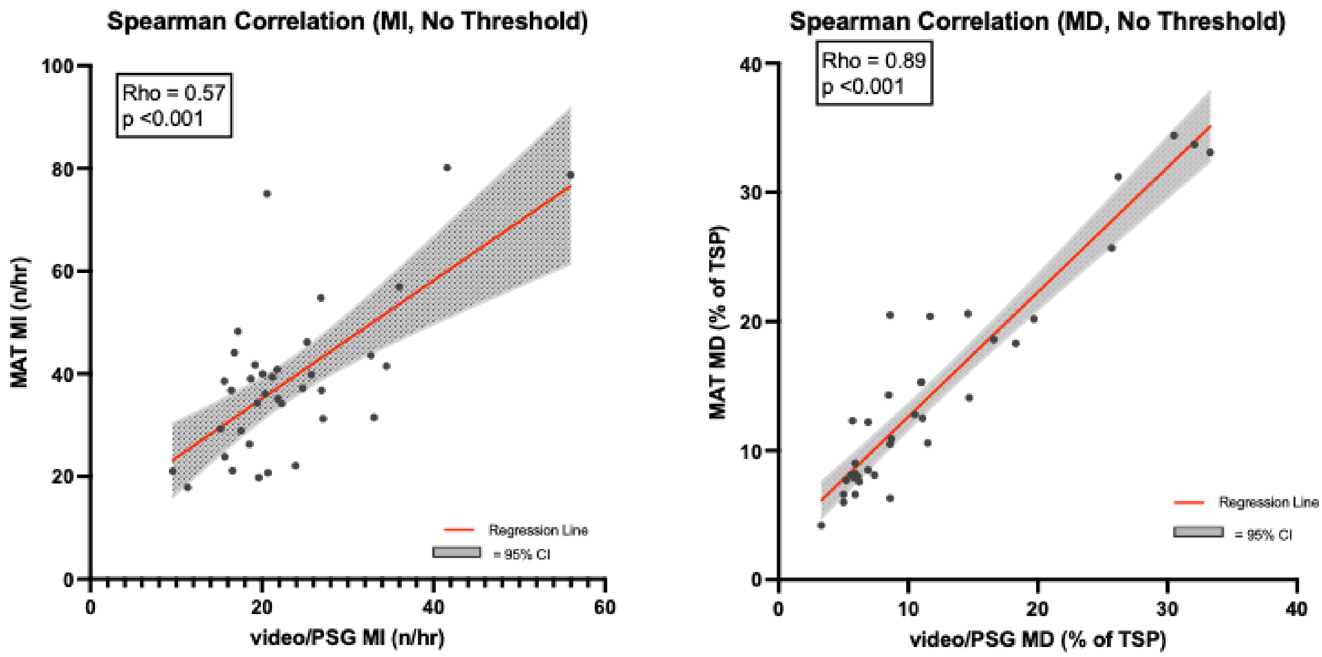
A moderate positive correlation was observed between the movement indices detected by the MAT and video/PSG across movements of any event duration (Spearman's r = 0.57, df = 34, p < 0.001). (***Table 7*** & ***Figure 5)*** This correlation strengthened to a strong level when a minimum movement duration threshold of 7 s was applied (Spearman's r = 0.80, p < 0.001).

Table 7: Correlation of Movement Index by thresholds

Comparison	Spearman ρ	p-value	df
Video/PSG MI 0 vs MAT MI 0	0.57	<0.001	34
Video/PSG MI 1 vs MAT MI 1	0.63	<0.001	34
Video/PSG MI 3 vs MAT MI 3	0.67	<0.001	34
Video/PSG MI 5 vs MAT MI 5	0.73	<0.001	34
Video/PSG MI 7 vs MAT MI 7	0.80	<0.001	34

Figure 5 Correlation of MI ***(a)*** and MD ***(b)*** between MAT and video/PSG – All movements (no threshold limit).

(a) (b)



Correlation for MI and MD at other time thresholds are presented in supplementary document (***supp figure 3***).

Using the parameters from the linear regression line a formula was devised to estimate the equivalent of MAT MI based on the video/PSG index for thresholds of 0, 1, 3,5 and 7 s. ***Table 8.***

Table 8: Linear equation for correlation between MAT MI based on video/PSG MI

Comparison	Linear Regression Equation
MI 0	y = 1.2x + 12.1
MI 1	y = 1.3x + 12.5
MI 3	y = 1.0x + 7.5
MI 5	y = 1.2x + 1.8
MI 7	y = 0.96x + 1.6

y: MAT MI, x: video/PSG MI

(b) MD

For total MD, there was a very strong positive correlation when no time threshold was applied (Spearman's r = 0.89, df = 34, p < 0.001). See ***Figure 5***. Correlations remained strong when the different duration thresholds were applied. See ***Table 9***.

Table 9: MD correlation by duration thresholds

Comparison	Spearman ρ	p-value	df
Video/PSG MD 0 vs MAT MD 0	0.89	<0.001	34
Video/PSG MD 1 vs MAT MD 1	0.89	<0.001	34
Video/PSG MD 3 vs MAT MD 3	0.90	<0.001	34
Video/PSG MD 5 vs MAT MD 5	0.91	<0.001	34
Video/PSG MD 7 vs MAT MD 7	0.91	<0.001	34

5. Comparison of MI and MD across Scoring Methods and Time Thresholds

We compared manual scoring and two automated Sonomat movement scoring methods against video/PSG and each other, across time thresholds of ≥1s, ≥3s and ≥5s:

(1) ***Video/PSG*** – manual scoring of movements based on rules described in methods
(2) ***Manual scoring Sonomat (MAT)*** – manual scoring of movements based on rules described in methods
(3) ***Sonoauto*** – the device's built-in automated detection algorithm, and
(4) ***Rules*auto** – the device scoring using a rules-based approach derived from our manual scoring criteria.

To satisfy the assumptions of normality and constant variance the outcomes (MI and MD) were Log_{10} transformed.

Movement Index (MI)

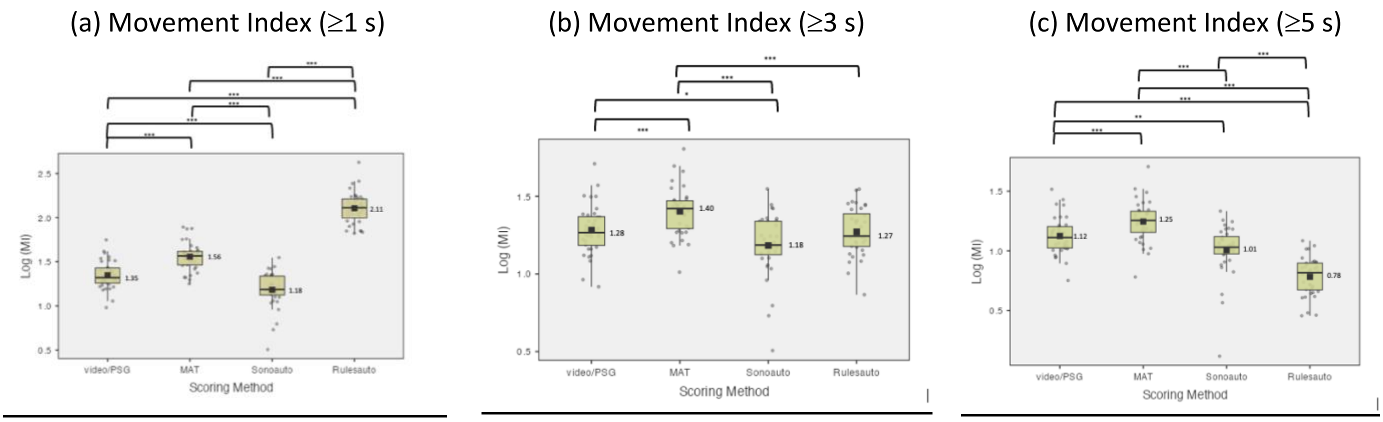
The mixed-effects model for $\log_{10}$ MI showed good fit (marginal $R^2 = 0.76$, conditional $R^2 = 0.89$). Most of the variance in the outcome is explained by the fixed effects. Scoring Method, Time (duration) Threshold and their interaction were all strongly associated with $\log_{10}$ MI (Scoring Method $F(3,385) = 136.0$, Time Threshold $F(2,385) = 692.5$, interaction $F(6,385) = 211.2$; all $p < 0.001$). Given that the two-way interaction between Method and time was significant, we report the interaction rather than the main effects, see ***supplementary Figure 4*** with output from Jamovi. MI declined modestly with increasing duration threshold for PSG, MAT and Sonoauto, whereas Rulesauto produced the highest MI at ≥1 s but the lowest MI at ≥5 s (Bonferroni-adjusted pairwise comparisons $p < 0.001$; see ***Figure 6***). ***Table 10*** reports the estimated marginal means (EMMs) with 95% CI for Log_{10} MI by scoring methods and time thresholds and the corresponding back transformed values on the original MI scale.

Table 10. Estimated marginal means back-transformed MI by scoring method and movement duration threshold. (* See ***Supplementary Table 2*** for EMM in Log_{10} MI)

Scoring Method	Time (duration) Threshold	MI (n/hr)	95% CI (n/hr)
Video/PSG	1	22.3	19.5-25.4
Video/PSG	3	19.2	16.8-21.9
Video/PSG	5	13.3	11.7-15.2
MAT	1	36.1	31.6-41.2
MAT	3	25.3	22.2-28.9
MAT	5	17.6	15.4-20.1
Sonoauto	1	15.3	13.3-17.4
Sonoauto	3	15.2	13.3-17.4
Sonoauto	5	10.1	8.9-11.6
Rulesauto	1	127.8	111.9-146.0
Rulesauto	3	18.7	16.4-21.4

Rulesauto	5	6.1	5.3-6.9

Figure 6 Movement Index video/PSG Vs MAT Vs Sonoauto Vs Rulesauto ***(a)*** ≥ 1 s, ***(b)*** ≥ 3 s and ***(c)*** ≥ 5 s



*Bonferroni-adjusted paired wise comparisons, * p < 0.05, ** p < 0.01, *** p < 0.001.*

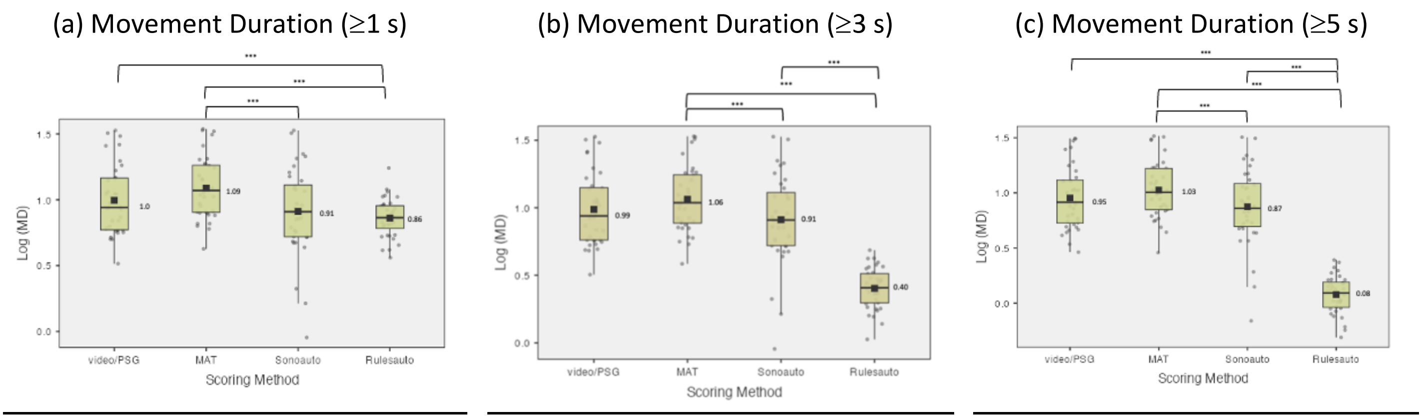
Movement Duration (MD)

For $\log_{10}$ MD, the mixed model also showed good fit (marginal $R^2 = 0.55$, conditional $R^2 = 0.89$; see supplementary for full results). The random intercept variance at the child level (0.05; SD 0.23) exceeded the residual variance (0.02; SD 0.13), yielding an ICC of 0.77 and indicating that most variability in movement duration was attributable to between-child differences. Scoring Method, Time Threshold and their interaction were again highly significant (Scoring Method $F(3,385) = 509.3$, Time Threshold $F(2,385) = 121.9$, interaction $F(6,385) = 78.0$; all $p < 0.001$). Given that the two-way interaction between Method and time was significant, we report the interaction rather than the main effects, see ***supplementary Figure 5*** with output from Jamovi. Estimated marginal means showed that video/PSG, MAT and Sonoauto gave broadly similar movement duration across thresholds, whereas Rulesauto showed a marked reduction at ≥3 s and ≥5 s and was significantly lower than the other methods at these thresholds (Bonferroni-adjusted $p < 0.001$; see ***Figure 7***). ***Table 11*** reports the estimated marginal means (EMMs) with 95% CI for Log_{10} MD by scoring methods and time thresholds and the corresponding back transformed values on the original MD scale.

Table 11: Estimated marginal means back-transformed to MD by scoring method and movement duration threshold. (* See ***Supplementary Table 3*** for EMM in Log_{10} MD)

Scoring Method	Time Threshold	MD (%)	95% CI MD (%)
Video/PSG	1	9.9	8.1-12.1
Video/PSG	3	9.7	8.0-11.9
Video/PSG	5	9.0	7.4-11.0
MAT	1	12.3	10.0-15.0
MAT	3	11.6	9.5-14.1
MAT	5	10.6	8.7-13.0
Sonoauto	1	8.2	6.7-10.0
Sonoauto	3	8.2	6.7-10.0
Sonoauto	5	7.5	6.1-9.1
Rulesauto	1	7.3	5.9-8.9
Rulesauto	3	2.5	2.1-3.1
Rulesauto	5	1.2	1.0-1.5

Figure 7 Movement Duration video/PSG Vs MAT Vs Sonoauto Vs Rulesauto ***(a)*** ≥ 1 s, ***(b)*** ≥ 3 s and ***(c)*** ≥ 5 s



*Bonferroni-adjusted paired wise comparisons, * p < 0.05, ** p < 0.01, *** p < 0.001.*

6. Inter-rater agreement (IRA) and Intraclass Correlation Coefficient (ICC) for Movement Scoring on Sonomat (Table 12)

Manual scoring showed the greatest event level concordance with Sonoauto (median IRA of 0.55, IQR 0.11, range 0.25-0.73), while concordance dropped to 0.43 for MAT vs Rulesauto and to 0.35 for Rulesauto vs Sonoauto. Despite these moderate IRA values, the nightly movement index ICC were uniformly poor for all pairs, indicating that simple event indices are not interchangeable across the methods. In contrast, the movement duration metric (% total sleep period) revealed good reliability for Sonoauto relative to MAT scoring (ICC 0.78, 95% CI 0.31-0.91, P<0.001), whereas Rulesauto demonstrated negligible agreement with either comparator. This suggests, Sonoauto approximates manual scoring for total movement time but still misses nearly half of the individual events, while the rule based algorithm (Rulesauto) fails on both event index and total time. With increasing movement duration thresholds, the ICC improved for MI across all comparisons for movements greater than 3 s but decreased for movements greater than 5 s. (***supp Table 1a***). For MD the ICC improved with increasing thresholds for MAT vs Sonoauto scoring but did not improve significantly for other comparisons. (***Supp Table 1b***)

Table 12: IRA and ICC between scoring methods (MAT Vs Sonoauto Vs Rulesauto) on Sonomat for all movements.

	IRA	ICC MI	ICC MD
MAT Vs Sonoauto	0.55 (0.11, 0.25-0.73)	0.15 (-0.084 – 0.43) p = 0.006	0.78 (0.31-0.91) P < 0.001
MAT Vs Rulesauto	0.43 (0.08, 0.28-0.56)	-0.011 (-0.098-0.13) p = 0.58	0.13 (-0.099-0.39) P = 0.11
Rulesauto Vs Sonoauto	0.35 (0.07, 0.26-0.43)	0.008 (-0.054-0.11) p = 0.42	0.26, (-0.04-0.53), P = 0.043

4.7 Discussion

The findings demonstrate that the Sonomat performs comparably to video/PSG in quantifying both the number and cumulative duration of body movements during sleep. The Sonomat detects greater numbers of shorter movements than video/PSG, suggesting it may detect a greater number of brief movement events than video/PSG.

Movement indices (MI) and duration (MD)

The MI reported in this study (both on the Sonomat and video/PSG) were markedly higher than those documented in previous literature. [24,61] The differences likely reflect variations in study populations and methodological approaches. Unlike prior studies that focused on healthy or restless children, this study examined symptomatic cohort with suspected sleep-disordered breathing. In addition, due to the Sonomat's inability to distinguish the anatomical origin of the movements, this study included all detected movements, both small and large body movements, regardless of type or location. Earlier research limited analysis to sleep-epoch movements based on conventional PSG scoring. In contrast, because the Sonomat cannot determine sleep-wake states, we assessed all movements occurring during the TSP as defined by PSG (with both studies analysed as a continuous recording, with no regard to epochs). This allowed for a direct and consistent comparison between the two modalities, with movement indices derived from equivalent time intervals. Consequently, all movement events (both asleep and wake) were included to provide a comprehensive evaluation of the Sonomat's performance relative to video/PSG.

Respiratory bands were included in this study to improve comparability with the Sonomat's signal detection method, which incorporates respiratory-derived signals. While respiratory bands are not part of the consensus criteria for scoring large body movements, the consensus paper acknowledged that signal changes in these channels can occur during movements.[60] In contrast, stethoscope signals from the Sonomat were excluded due to their vulnerability to artifacts from non-respiratory sources, such as the gut or heart sounds, which could compromise scoring accuracy.

This study did not apply an initial individual movement duration threshold to capture brief movements, in contrast to prior literature that used cut-offs of 1 s [24] or 3 s. [60] This approach enabled the inclusion of leg movements, which the AASM defines as lasting as briefly as 0.5 s.[134,139] Additionally, it allowed an open exploration of how the Sonomat, as a novel technology, detects sleep-related movements.

As the movement duration threshold increased, the difference in MI between Sonomat and video/PSG became statistically nonsignificant for movements exceeding 7 s duration. For movements of all durations, a mean difference of 2.1% in total MD is equivalent to 11 minutes out of the median TSP of 498 minutes. Total MD remained significantly different between the two systems, although at the threshold of individual movements greater than 7 s, the clinical relevance of a 0.9% difference in the median TSP, equivalent to approximately 4.5 minutes, remains unclear and warrants further investigation.

The consistently higher detection of movement events and longer cumulative duration determined by the Sonomat studies likely reflects a combination of differences in sensor configuration, signal processing sensitivity, and scoring rules compared to videoPSG. The Sonomat includes four dedicated movement sensors that detect subtle pressure shifts across the mat surface, requiring event confirmation across multiple channels. In contrast, video/PSG identifies movements based on signal changes across some channels that are primarily designed for other physiological measures, such as EEG, which are not acquired or filtered with the purpose of capturing body movements. De Meo et al. addressed the significance of detecting EMG-based movements that do not necessarily involve visible motion on video.[61] Drawing on comparisons with periodic leg movements (PLM), defined solely by EMG activity, they argued that such events remain physiologically meaningful.[61] These events have been linked to changes in heart rate, EEG changes, blood pressure elevations, and cerebral hemodynamic alterations,[61] supporting their clinical relevance even when not accompanied by movements observable on video. For this reason, we chose to use both video and signal changes on PSG to score body movements.

Traditional PSG systems often incorporate signal filtering which may also attenuate brief or low-amplitude movements. In contrast, the Sonomat does not apply such filtering criteria, which could contribute to a higher overall movement detection.

The Sonomat may also detect external factors such as environmental noise or movements from a bed partner, which could potentially inflate the recorded movement count and overall duration. To mitigate this, the study required confirmation across at least two signal channels to reduce artefactual detection, though this strategy may not eliminate such influences entirely.

Finally, some variability in manual scoring, especially at the margins of movement start and end (whether video/PSG or MAT), could also contribute to discrepancies.

The systematically higher movement counts detected by the Sonomat may relate to a combination of the physical properties of the two study types, and differences in the methods of data acquisition and analysis. Because the Sonomat extends across the full sleeping surface, it may capture subtle weight shifts and low-amplitude postural adjustments that do not produce visible movement on video or EEG/EMG artefact detectable by PSG scoring. Furthermore, signal processing differs between the two systems—including sampling filter settings, and event detection thresholds—and this may contribute to systematic differences in event counts that are independent of true movement frequency. The sampling rates of the Sonomat are higher than those traditionally used for PSG at 250 Hz for movement and 4 kHz for acoustic signals. The extent to which these factors contributed to the observed discrepancy cannot be fully determined from the current data.

Matching of movements and correlation between Sonomat and video/PSG

The Sonomat captured a greater proportion of the movements identified by video/PSG than the reverse. The agreement between the two systems was highest for movements lasting more than 5 s. At the 3-s threshold, the agreement rate was 88%, which is lower than the reported 95% concordance for video/PSG versus vPSG (video-only movement scoring) at the same threshold.[61] This difference is not unexpected, given that PSG and vPSG utilize nearly identical physiological signals apart from video, while Sonomat and PSG use different sensing mechanisms.

Although absolute movement duration remained statistically different across all thresholds, the strong correlations in duration suggest that children who move frequently are likely to be consistently identified by both modalities. This supports the potential of the Sonomat as a screening tool for sleep related restlessness. Correlation in MI was more modest but improved when the analysis was restricted to movements longer than 7 s. These findings suggest the need for either applying a correction factor or developing device-specific normative reference ranges when using the Sonomat to define clinical thresholds. By contrast, MD correlated strongly across all event thresholds, indicating it is a more robust measure with less device-specific variability.

De Meo et al, used the linear regression parameters to define a higher threshold of large muscle movements scored on PSG (>6/hr) when compared to video (>5/hr) to determine restless sleep disorder (RSD). [61] Since there are no established diagnostic thresholds using the scoring method described in this study, no clinical cut-offs were determined. Using parameters derived from the linear regression analysis, formulas were developed to estimate the equivalent Sonomat Movement Index values based on video/PSG indices for thresholds of 0, 1, 3, 5 and 7 s. (***Table 7***). These formulas may serve as a reference for future research or clinical applications, but their utility requires further validation.

Across the five duration threshold settings (0 to 7s), the Sonomat captured the great majority of video/PSG-defined movements: median event-level matching ranged from 88% to 91% (***Table 4)*** at thresholds 0–5 s and remained 85% at threshold of 7 s. In the reverse direction, video/PSG confirmed only about half of the Sonomat events at the lowest thresholds (49–50%) but this rose to 79% at threshold of 7 s. Importantly, the movements shared by both systems accounted for almost all video/PSG movement time (median 97% at no threshold) and for 85–92% of total Sonomat movement time. (***Table 5***) Thus, although video/PSG fails to register 20–50% of Sonomat-detected events, those missed events are brief, contributing ≤ 15% of the Sonomat's aggregate movement duration. This pattern indicates that both systems detected the same core set of video/PSG-defined movements, while the Sonomat detected an additional subset of shorter duration events not identified by video/PSG.

Comparison of movement metrics across scoring methods and thresholds

The linear mixed-effects models extend the agreement analyses by describing how each scoring method behaves across movement duration thresholds. For movement index, video/PSG, MAT and Sonoauto showed similar trajectories as the minimum duration increased from ≥ 1 s to ≥ 5 s, with MI falling gradually across all three methods. On the original scale, MAT yielded consistently higher MI than video/PSG, whereas Sonoauto produced slightly lower values. These differences are consistent with variation in how human scorers and the device algorithm segment individual events, but the overall pattern suggests that all three approaches capture a comparable burden of appreciable body movements during sleep.

In contrast, Rulesauto behaved differently. At the ≥ 1 s threshold, Rulesauto produced MI values more than five-fold higher than video/PSG and several-fold higher than either MAT or Sonoauto, indicating substantial over-detection of brief movements. As the duration threshold increased, MI for Rulesauto declined much more steeply than for the other methods, such that by ≥ 5 s its MI was lower than that of video/PSG, MAT and Sonoauto. This pattern is compatible with a rules-based algorithm that fragments movement into many short events when the baseline signal is low, but fails to preserve event continuity once stricter duration criteria are applied. In practice, this threshold sensitivity means that MI derived from Rulesauto cannot be interpreted interchangeably with MI obtained from video/PSG, manual Sonomat scoring or Sonoauto.

Movement duration showed a more stable profile. Across the movement duration thresholds, video/PSG, MAT and Sonoauto each estimated that children spent approximately 8–12% of TST moving, with only modest reductions in MD at higher thresholds. Sonoauto again tracked manual scoring closely, with slightly lower MD than manual scoring (MAT) and values similar to video/PSG. In contrast, Rulesauto yielded substantially shorter movement time at thresholds of ≥3 s and ≥ 5 s, with MD falling to around 2–3% and 1–2% of total sleep period, respectively. When considered alongside the inflated MI at low thresholds, these findings indicate that Rulesauto identifies many very brief deflections that contribute little to total movement time. This combination of high MI and low MD at stricter thresholds may lead to misclassification of restlessness in sleep.

Variance components indicate substantial between-child clustering (≈50% for log-MI; ≈75% for log-MD). This pattern suggests that both indices capture trait-like aspects of movement during sleep, but that movement duration is a more stable characteristic within a given child than the number of scored events. This is consistent with the inter-rater analyses, in which MD showed substantially higher reliability than MI between manual Sonomat scoring and Sonoauto. Taken together, the modelling and agreement results support the use of MD as the primary summary metric when comparing across scoring paradigms, with MI reserved for within-method analyses or for applications where event-level features (such as periodicity) are central.

Concordance between scoring methods

Concordance between different scoring methods on the Sonomat showed that the Sonoauto algorithm had only moderate alignment with manual scoring on a per event basis (IRA 0.55). Reliability between Sonoauto and manual scoring was low for movement index (ICC 0.15) but higher for movement duration (ICC 0.77), suggesting discrepancies in event segmentation while still capturing the overall movement burden. The ICC for movement index was comparatively lower than previously reported values for periodic limb movement scoring in adults, where automated systems demonstrated strong agreement with manual scoring (0.78-1.0, p<0.001).[140] In contrast, Camacho et al reported only moderate agreement in children (ICC 0.63, 95% CI:0.51-0.72), indicating that lower concordance in paediatric populations may be expected.[141] The mixed-model results complement these observations by demonstrating that, despite poor event-level reliability, Sonoauto reproduces the pattern of MI and MD across thresholds seen with manual scoring and does not exhibit the marked threshold dependence observed with Rulesauto.

The Rulesauto method performed markedly worse, frequently mismatching events and showing poor reliability for both MI and MD compared to the other two methods. A key observation was the markedly inflated MI reported by Rulesauto at lower movement thresholds. This custom algorithm consistently detected more movements than either manual or Sonoauto scoring. The discrepancy likely stems from the fundamental difference between a rigid, rule-based system and the more nuanced, context-aware approach employed by human scorers. In periods of quiescence, the baseline signal drops significantly, making the algorithm overly sensitive to minor physiological changes such as a single deep breath. Additionally, it tends to register each signal spike as an individual movement event, whereas human scorers are more likely to interpret a cluster of spikes as a single, continuous movement.

The threshold analyses also provide guidance for practical scoring. For MI, inter-rater ICCs improved when only movements longer than 3 s were included but deteriorated when the threshold was increased to 5 s, suggesting that removing very brief movement reduces noise, whereas excluding 3 s movements removes clinically relevant signal. For MD agreement between MAT and Sonoauto improved modestly with increasing thresholds, while comparisons involving Rulesauto showed little or no benefit. Together with the mixed-model findings, these patterns support the use of video/PSG or manual Sonomat scoring, and potentially Sonoauto, with a minimum movement duration of around 3 s when quantifying night-long movement. These also indicate that the current Rulesauto implementation is not suitable for clinical or research use without substantial revision.

The ability of the Sonomat to detect movements non-invasively aligns with the clinical need for less intrusive, patient-friendly monitoring methods, particularly in paediatric populations where tolerance to traditional PSG setups can be challenging.[7]

An important strength of this study is the comprehensive comparison between Sonomat and video/PSG, including synchronized data analysis and sensitivity testing using different threshold cut offs. Nonetheless, several limitations should be acknowledged. The retrospective design and small sample size may limit the generalizability of the results. Although the sample size was modest, the analysis was strengthened by a high number of detected events (7023 total movement events by video/PSG and 11476 by Sonomat). Additionally, the study cohort consisted of symptomatic children undergoing evaluation for suspected OSA and did not include children selected for restlessness, nor were there any control subjects. Therefore, these findings may not fully capture the movement features characteristic of restless sleep. Additionally, the data was collected before the formal diagnostic criteria for restless sleep disorder were stablished.

Several additional limitations warrant acknowledgement. First, signal noise may have contributed to false-positive movement detections on the Sonomat, and this cannot be fully separated from true movement events using the automated detection algorithm alone. Those affecting acoustic channels (sheet friction, clothing contact, or ambient environmental sounds) would have required movement on one of the movement detection channels, but those movements may occur secondary to (rather than in association with) the noise. Second, inclusion in this study required good signal quality, which may have introduced selection bias toward participants with lower movement burden or more stable recordings, as discussed in Chapter 3. Third, and most importantly, this study lacked an independent validated ground-truth measure of body movement. Without a reference standard such as video-based body movement coding by trained observers, it is not possible to unambiguously attribute the higher Sonomat counts to greater sensitivity to true movement events rather than to a higher false-positive detection rate. Future work should include simultaneous video capture specifically designed to validate movement event counts.

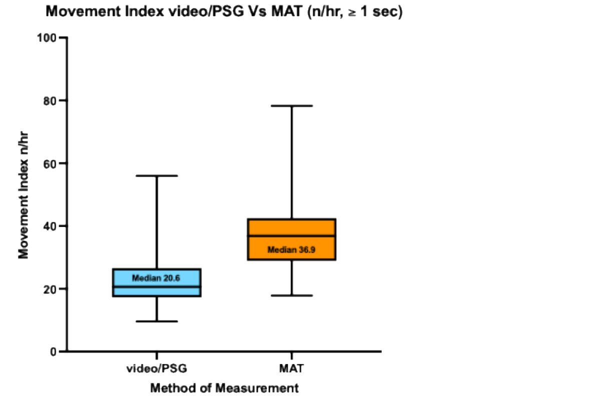
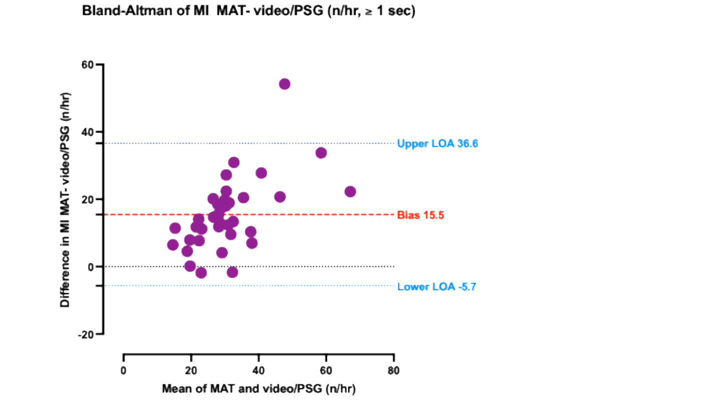
Although the Sonomat captured a longer total movement duration and identified a greater number of short-duration movements, the clinical significance of these additional events and time remains uncertain. Further research is needed to determine whether increased detection of movements corresponds to meaningful differences in sleep quality or daytime functioning. Future studies should also investigate the use of the Sonomat for assessing night to night variability in movement within home settings, establish normal indices across age groups and explore its role in measuring movements in other conditions.

4.8 Conclusion

The Sonomat detected a greater number of brief movements and yielded higher overall movement burden estimates than video/PSG, with detection rates converging for longer duration events. It demonstrates greater detection of shorter duration events, and detection rates become comparable to video/PSG for longer duration movements. When establishing clinical thresholds, either correction factors should be applied when translating from video/PSG data or device-specific normative reference ranges should be developed. The Sonomat's capacity to capture movement without direct patient contact may complement video/PSG in contexts where full polysomnography is unavailable. This study also highlights the potential role of automated scoring in streamlining movement detection. The built-in algorithm (Sonoauto) performed comparably to manual scoring in terms of MD, although event level agreement and MI reliability were lower. These findings suggest that while automated methods may support efficiency in data processing, further refinement and validation are needed before they can fully replace manual scoring in clinical applications.

4.9 Supplementary to Chapter 4: Measuring Body Movements During Sleep: Sonomat Versus Polysomnography.

Supp Figure 1. Movement Index Box Plot and Bland Altman Plots by thresholds (1, 3, 5 and 7 s)

<table>
<tr><th></th><th>Movement Index video/PSG Vs MAT Box Plot</th><th>Movement Index video/PSG Vs MAT Bland Altman Plot</th></tr>
<tr><td>Threshold ≥ 1 s</td><td>
</td><td>
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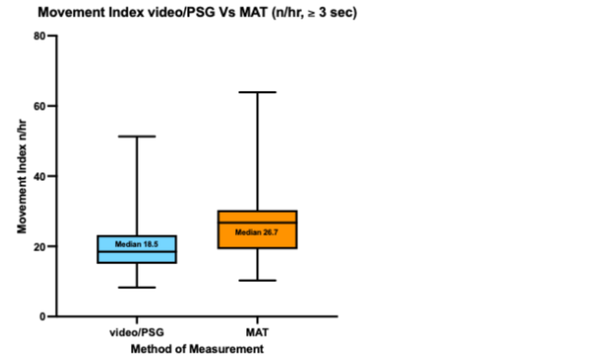
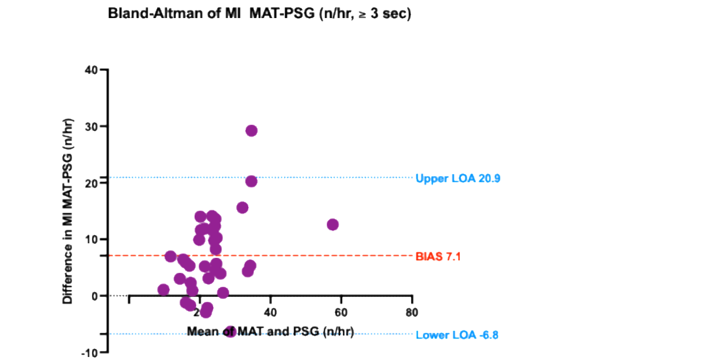
<tr><td>Threshold ≥ 3 s</td><td>
</td><td>
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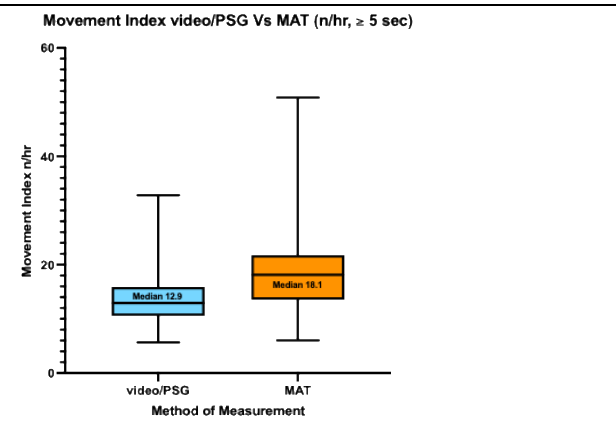
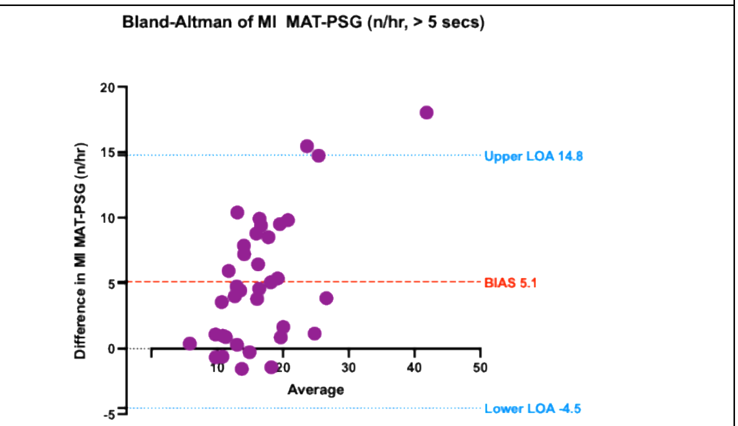
<tr><td>Threshold ≥ 5 s</td><td>
</td><td>
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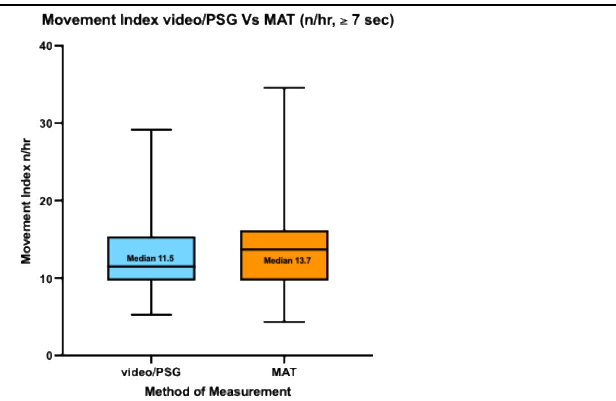
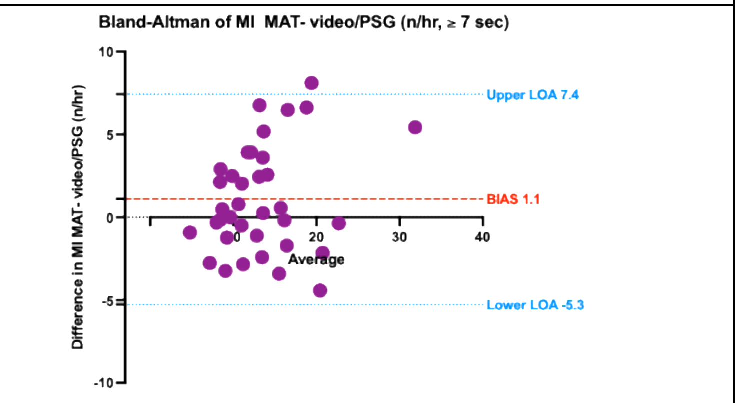
<tr><td>Threshold ≥ 7 secs</td><td>
</td><td>
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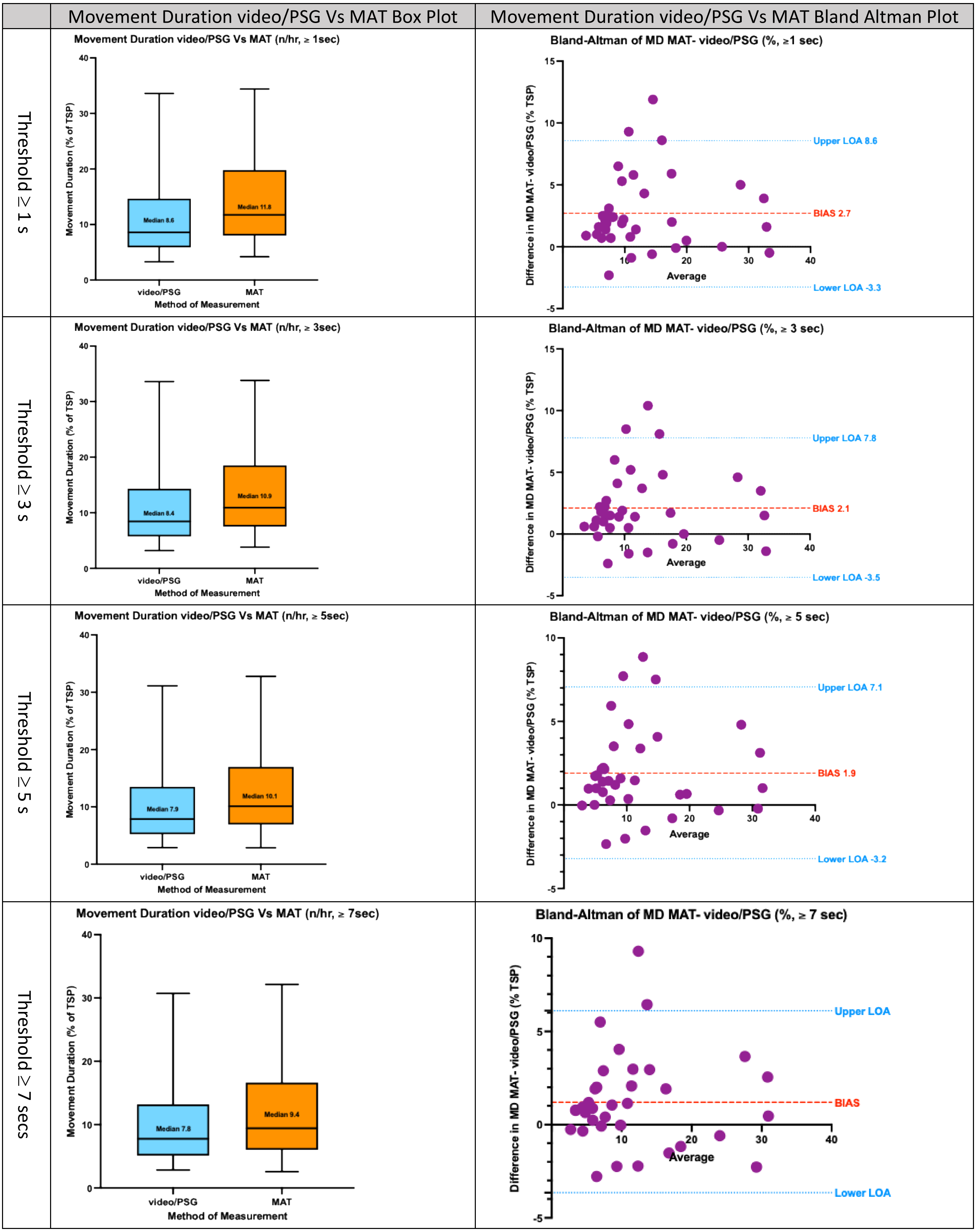
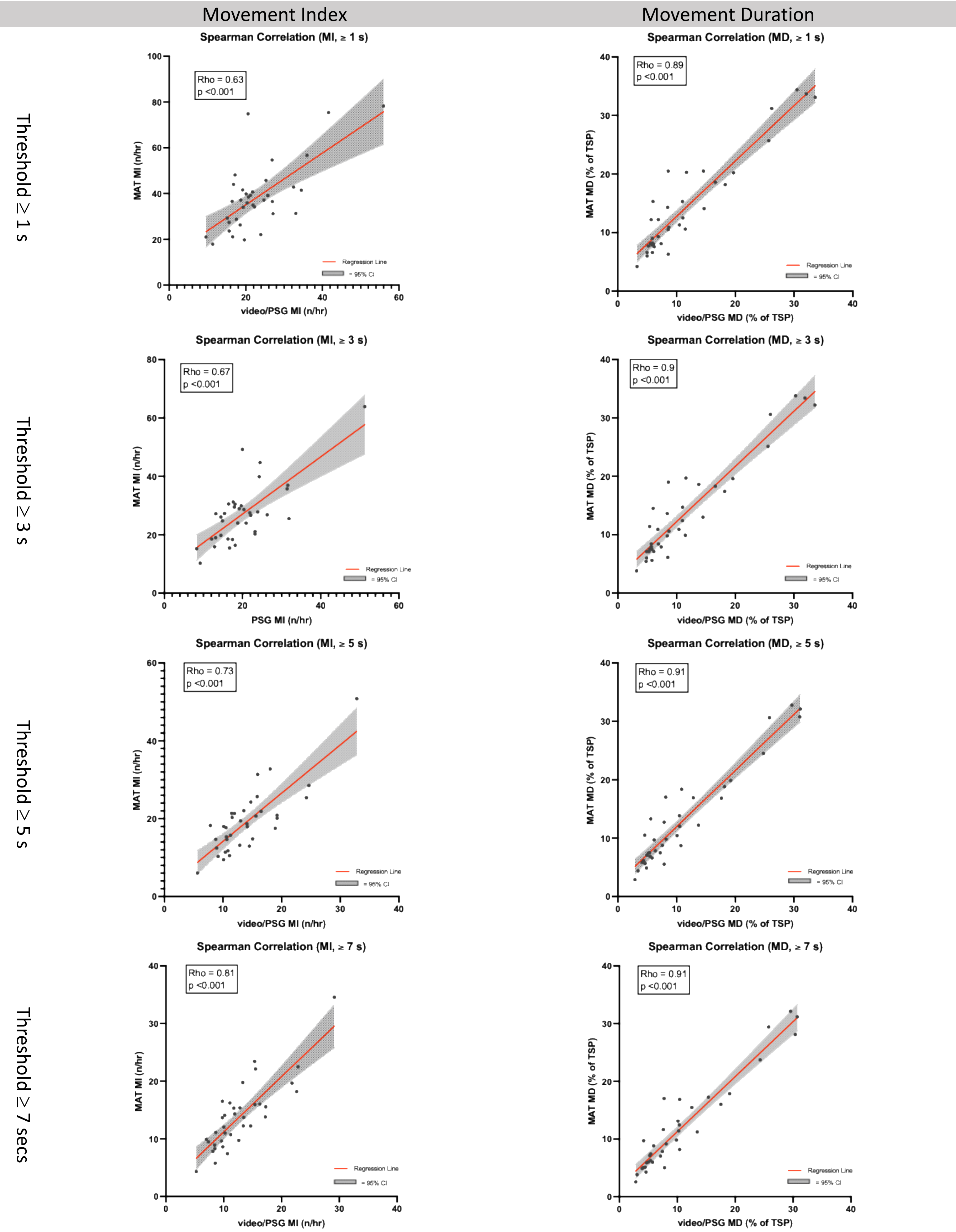
Figure 2. Movement Duration Box Plot and Bland Altman Plots by duration thresholds (1, 3, 5 and 7 s)



Supp Figure 3. Correlation Graphs Movement Index and Movement Duration: MAT Vs video/PSG (All Thresholds)



Formal outlier analysis of the correlation data presented in Supplementary Figure 3 was not performed in the current study. Future analyses should identify individual participants or recording sessions with values ≥2 SD from the group mean, to determine whether specific recordings disproportionately drive the observed inter-device correlations between Sonomat and video/PSG movement metrics.

Supp Table 1a: Intraclass Coefficient (ICC) for Movement Index at Thresholds ≥ 1, 3 and 5 s

Comparison	ICC MI 1 (CI)	ICC MI 3 (CI)	ICC MI 5 (CI)
Manual Vs Sonoauto	0.15 (-0.084 – 0.44) p =0.004	0.38 (-0.10 – 0.70) p < 0.001	0.33 (-0.10 – 0.65) p <0.001
Manual Vs Rulesauto	-0.009 (-0.096-0.13) p = 0.57	0.49 (-0.008 – 0.76) p <0.001	0.11 (-0.074 – 0.36 p = 0.015
Rulesauto Vs Sonoauto	0.0084 (0.054-0.11) p = 0.42	0.64 (0.30 – 0.81) p < 0.001	0.28 (-0.10 – 0.62) p <0.001

Supp Table 1b: Intraclass Coefficient (ICC) for Movement Duration at Thresholds ≥ 1, 3 and 5 s

Comparison	ICC MD 1 (CI)	ICC MD 3 (CI)	ICC MD 5 (CI)
Manual Vs Sonoauto	0.78, (0.31-0.91), p <0.001	0.81 (0.47-0.92) p <0.001	0.82 (0.52 – 0.92) p < 0.001
Manual Vs Rulesauto	0.14 (-0.098 – 0.39) p = 0.11	0.066 (-0.075 – 0.26) p = 0.15	0.023 (-0.076 – 0.17) p = 0.35
Rulesauto Vs Sonoauto	0.26 (-0.4 - 0.53) p = 0.043	0.099 (-0.091 – 0.33) p = 0.12	0.038 (-0.094 – 0.22) p = 0.31

Supp Table 2. Linear Mixed Model Log_{10} MI – Jamovi Output

Fixed Effects Omnibus Tests

	F	df	df (res)	p
Scoring Method	136	3	385	4.26e0-60
Time Threshold	693	2	385	2.93e-128
Scoring Method ✻ Time Threshold	211	6	385	1.82e-118

Parameter Estimates (Fixed coefficients)

				95% Confidence Intervals				
Names	Effect	Estimate	SE	Lower	Upper	df	t	p
(Intercept)	(Intercept)	1.2912	0.0225	1.2470	1.3354	35.0	57.42	3.17e0-36
Scoring Method1	MAT - video/PSG	0.1505	0.0158	0.1194	0.1815	385.0	9.53	1.85e0-19
Scoring Method2	Sonoauto - video/PSG	-0.1275	0.0158	-0.1585	-0.0964	385.0	-8.07	8.99e0-15
Scoring Method3	Rulesauto - video/PSG	0.1351	0.0158	0.1041	0.1662	385.0	8.56	2.79e0-16
Time Threshold1	3 - 1	-0.2635	0.0137	-0.2903	-0.2366	385.0	-19.26	2.21e0-58
Time Threshold2	5 - 1	-0.5089	0.0137	-0.5358	-0.4820	385.0	-37.21	1.43e-129
Scoring Method1 ✻ Time Threshold1	(MAT - video/PSG) ✻ (3 - 1)	-0.0891	0.0387	-0.1651	-0.0131	385.0	-2.30	0.0218

Parameter Estimates (Fixed coefficients)

Names	Effect	Estimate	SE	95% Confidence Intervals Lower	Upper	df	t	p
Scoring Method2 ✻ Time Threshold1	(Sonoauto - video/PSG) ✻ (3 - 1)	0.0648	0.0387	-0.0112	0.1408	385.0	1.68	0.0947
Scoring Method3 ✻ Time Threshold1	(Rulesauto - video/PSG) ✻ (3 - 1)	-0.7701	0.0387	-0.8461	-0.6940	385.0	-19.91	3.94e0-61
Scoring Method1 ✻ Time Threshold2	(MAT - video/PSG) ✻ (5 - 1)	-0.0890	0.0387	-0.1650	-0.0130	385.0	-2.30	0.0220
Scoring Method2 ✻ Time Threshold2	(Sonoauto - video/PSG) ✻ (5 - 1)	0.0453	0.0387	-0.0307	0.1213	385.0	1.17	0.2424
Scoring Method3 ✻ Time Threshold2	(Rulesauto - video/PSG) ✻ (5 - 1)	-1.1016	0.0387	-1.1777	-1.0256	385.0	-28.48	8.60e0-97

Post Hoc Tests

Post Hoc comparison: Scoring Method ✻ Time Threshold (ONLY Relevant Comparisons are displayed)

Comparison Scoring Method	Time Threshold	vs	Scoring Method	Time Threshold	Difference	SE	95% Confidence Intervals Lower	Upper	t	df	$p_{bonferroni}$
video/PSG	1	-	MAT	1	-0.2098	0.0274	-0.26361	-0.15604	-7.67057	385	9.35e0-12
video/PSG	1	-	Sonoauto	1	0.1642	0.0274	0.11038	0.21795	6.00147	385	2.98e00-7
video/PSG	1	-	Rulesauto	1	-0.7590	0.0274	-0.81282	-0.70526	-27.74839	385	4.70e0-92
video/PSG	3	-	MAT	3	-0.1207	0.0274	-0.17451	-0.06695	-4.41354	385	8.73e00-4
video/PSG	3	-	Sonoauto	3	0.0994	0.0274	0.04558	0.15315	3.63247	385	0.02104
video/PSG	3	-	Rulesauto	3	0.0110	0.0274	-0.04277	0.06479	0.40254	385	1.00000
video/PSG	5	-	MAT	5	-0.1208	0.0274	-0.17461	-0.06705	-4.41727	385	8.59e00-4
video/PSG	5	-	Sonoauto	5	0.1189	0.0274	0.06509	0.17265	4.34558	385	0.00117

Post Hoc comparison: Scoring Method ✻ Time Threshold (ONLY Relevant Comparisons are displayed)

Comparison							95% Confidence Intervals				
Scoring Method	Time Threshold	vs	Scoring Method	Time Threshold	Difference	SE	Lower	Upper	t	df	$p_{bonferroni}$
video/PSG	5	-	Rulesauto	5	0.3426	0.0274	0.28881	0.39638	12.52438	385	1.33e0-28
MAT	1	-	Sonoauto	1	0.3740	0.0274	0.32021	0.42777	13.67204	385	3.82e0-33
MAT	1	-	Rulesauto	1	-0.5492	0.0274	-0.60300	-0.49544	-20.07782	385	4.79e0-60
MAT	3	-	Sonoauto	3	0.2201	0.0274	0.16631	0.27388	8.04601	385	7.07e0-13
MAT	3	-	Rulesauto	3	0.1317	0.0274	0.07796	0.18552	4.81608	385	1.39e00-4
MAT	5	-	Sonoauto	5	0.2397	0.0274	0.18592	0.29349	8.76285	385	4.06e0-15
MAT	5	-	Rulesauto	5	0.4634	0.0274	0.40965	0.51721	16.94165	385	1.10e0-46
Sonoauto	1	-	Rulesauto	1	-0.9232	0.0274	-0.97699	-0.86943	-33.74986	385	2.92e-115
Sonoauto	3	-	Rulesauto	3	-0.0884	0.0274	-0.14214	-0.03457	-3.22993	385	0.08874
Sonoauto	5	-	Rulesauto	5	0.2237	0.0274	0.16994	0.27751	8.17880	385	2.78e0-13

Estimate Marginal Means - Scoring Method ✻ Time Threshold

					95% Confidence Intervals	
Scoring Method	Time Threshold	Mean	SE	df	Lower	Upper
video/PSG	1	1.347	0.0291	94.6	1.290	1.405
video/PSG	3	1.283	0.0291	94.6	1.225	1.340
video/PSG	5	1.125	0.0291	94.6	1.067	1.183
MAT	1	1.557	0.0291	94.6	1.499	1.615
MAT	3	1.403	0.0291	94.6	1.345	1.461
MAT	5	1.246	0.0291	94.6	1.188	1.304
Sonoauto	1	1.183	0.0291	94.6	1.125	1.241
Sonoauto	3	1.183	0.0291	94.6	1.125	1.241
Sonoauto	5	1.006	0.0291	94.6	0.948	1.064
Rulesauto	1	2.106	0.0291	94.6	2.049	2.164
Rulesauto	3	1.272	0.0291	94.6	1.214	1.329
Rulesauto	5	0.782	0.0291	94.6	0.724	0.840

Supp Table 3. Linear Mixed Model Log_{10} MD – Jamovi Output

Fixed Effects Omnibus Tests

	F	df	df (res)	p
Scoring Method	509.3	3	385	1.31e-133
Time Threshold	121.9	2	385	9.97e0-42
Scoring Method ✻ Time Threshold	78.0	6	385	1.79e0-63

Parameter Estimates (Fixed coefficients)

				95% Confidence Intervals				
Names	Effect	Estimate	SE	Lower	Upper	df	t	p
(Intercept)	(Intercept)	0.84636	0.0386	0.7704	0.9223	35.0	21.909	5.08e0-22
Scoring Method1	MAT - video/PSG	0.07992	0.0172	0.0462	0.1136	385.0	4.659	4.38e00-6
Scoring Method2	Sonoauto - video/PSG	-0.08021	0.0172	-0.1139	-0.0465	385.0	-4.676	4.06e00-6
Scoring Method3	Rulesauto - video/PSG	-0.53174	0.0172	-0.5655	-0.4980	385.0	-30.999	1.11e-106
Time Threshold1	3 - 1	-0.12292	0.0149	-0.1521	-0.0937	385.0	-8.274	2.14e0-15
Time Threshold2	5 - 1	-0.23177	0.0149	-0.2610	-0.2026	385.0	-15.602	7.10e0-43
Scoring Method1 ✻ Time Threshold1	(MAT - video/PSG) ✻ (3 - 1)	-0.01781	0.0420	-0.1004	0.0648	385.0	-0.424	0.672
Scoring Method2 ✻ Time Threshold1	(Sonoauto - video/PSG) ✻ (3 - 1)	0.00809	0.0420	-0.0745	0.0907	385.0	0.193	0.847
Scoring Method3 ✻ Time Threshold1	(Rulesauto - video/PSG) ✻ (3 - 1)	-0.44992	0.0420	-0.5325	-0.3673	385.0	-10.708	1.35e0-23
Scoring Method1 ✻ Time Threshold2	(MAT - video/PSG) ✻ (5 - 1)	-0.02054	0.0420	-0.1031	0.0620	385.0	-0.489	0.625
Scoring Method2 ✻ Time Threshold2	(Sonoauto - video/PSG) ✻ (5 - 1)	0.00507	0.0420	-0.0775	0.0877	385.0	0.121	0.904
Scoring Method3 ✻ Time Threshold2	(Rulesauto - video/PSG) ✻ (5 - 1)	-0.74131	0.0420	-0.8239	-0.6587	385.0	-17.643	1.78e0-51

Post Hoc comparison: Scoring Method ✻ Time Threshold (ONLY Relevant Comparisons are displayed).

Comparison							95% Confidence Intervals				
Scoring Method	Time Threshold	vs	Scoring Method	Time Threshold	Difference	SE	Lower	Upper	t	df	$p_{bonferroni}$
video/PSG	1	-	MAT	1	-0.09270	0.0297	-0.15112	-0.03429	-3.12021	385	0.12827
video/PSG	1	-	Sonoauto	1	0.08459	0.0297	0.02618	0.14301	2.84724	385	0.30665
video/PSG	1	-	Rulesauto	1	0.13467	0.0297	0.07625	0.19308	4.53262	385	5.14e00-4
video/PSG	3	-	MAT	3	-0.07489	0.0297	-0.13331	-0.01648	-2.52076	385	0.79947
video/PSG	3	-	Sonoauto	3	0.07650	0.0297	0.01808	0.13492	2.57479	385	0.68659
video/PSG	3	-	Rulesauto	3	0.58459	0.0297	0.52617	0.64300	19.67580	385	2.50e0-58
video/PSG	5	-	MAT	5	-0.07216	0.0297	-0.13058	-0.01375	-2.42878	385	1.00000
video/PSG	5	-	Sonoauto	5	0.07953	0.0297	0.02111	0.13794	2.67674	385	0.51164
video/PSG	5	-	Rulesauto	5	0.87597	0.0297	0.81756	0.93439	29.48318	385	5.88e0-99
MAT	1	-	Sonoauto	1	0.17730	0.0297	0.11888	0.23571	5.96746	385	3.61e00-7
MAT	1	-	Rulesauto	1	0.22737	0.0297	0.16896	0.28579	7.65283	385	1.05e0-11
MAT	3	-	Sonoauto	3	0.15139	0.0297	0.09298	0.20981	5.09555	385	3.60e00-5
MAT	3	-	Rulesauto	3	0.65948	0.0297	0.60107	0.71790	22.19657	385	4.58e0-69
MAT	5	-	Sonoauto	5	0.15169	0.0297	0.09327	0.21011	5.10552	385	3.43e00-5
MAT	5	-	Rulesauto	5	0.94814	0.0297	0.88972	1.00655	31.91196	385	2.33e-108
Sonoauto	1	-	Rulesauto	1	0.05007	0.0297	-0.00834	0.10849	1.68538	385	1.00000
Sonoauto	3	-	Rulesauto	3	0.50809	0.0297	0.44967	0.56650	17.10102	385	2.33e0-47
Sonoauto	5	-	Rulesauto	5	0.79645	0.0297	0.73803	0.85486	26.80644	385	3.03e0-88

Estimate Marginal Means - Scoring Method ✻ Time Threshold

					95% Confidence Intervals	
Scoring Method	Time Threshold	Mean	SE	df	Lower	Upper
video/PSG	1	0.9962	0.0436	56.2	0.90899	1.083
video/PSG	3	0.9882	0.0436	56.2	0.90098	1.075
video/PSG	5	0.9537	0.0436	56.2	0.86641	1.041
MAT	1	1.0889	0.0436	56.2	1.00169	1.176
MAT	3	1.0631	0.0436	56.2	0.97587	1.150
MAT	5	1.0258	0.0436	56.2	0.93857	1.113
Sonoauto	1	0.9116	0.0436	56.2	0.82440	0.999
Sonoauto	3	0.9117	0.0436	56.2	0.82448	0.999
Sonoauto	5	0.8741	0.0436	56.2	0.78688	0.961
Rulesauto	1	0.8616	0.0436	56.2	0.77432	0.949
Rulesauto	3	0.4036	0.0436	56.2	0.31639	0.491
Rulesauto	5	0.0777	0.0436	56.2	-0.00956	0.165

Chapter 5: Sleep Movements and Obstructive Sleep Apnoea In Children Assessed by Sonomat and Polysomnography

5.1 Chapter Overview

This chapter tests whether (1) the movement burden differs by OSA status and (2) whether Movement Index (MI) or Movement Duration (MD) add value within the McGill score 1 subgroup. Using the thesis core methods (TSP denominator; MI events/hr, MD %), we compared groups and evaluated movement parameters by OSA status. In this cohort, MI and MD showed no significant between group differences and did not improve McGill 1 classification. These results potentially constrain movement metrics to measurement/phenotyping roles rather than diagnostic discrimination.

5.2 Introduction

Obstructive sleep apnoea has been reported to be present in up to 1-4% of the paediatric population.[142] It is associated with neurobehavioural symptoms, impaired growth, and adverse cardiovascular outcomes.[143-145] Snoring is the most common nocturnal symptom, however, parents frequently report restless sleep with frequent body movements as part of the sleep history.[146,147]

A recent systematic review showed that up to 81% of children with OSA exhibit restless sleep.[1] Current guidelines recommend screening for OSA in children who snore or present with restless sleep, hyperactivity, or anatomical risk factors such as adenotonsillar hypertrophy.[148,149]

Despite being a frequent complaint, “restless sleep” is not routinely or systematically measured in paediatric sleep studies. Modalities such as video-PSG, static charge–sensitive beds and actigraphy, have been used to measure nocturnal body movements, yet scoring approaches remain highly heterogeneous.[150] The IRLSS recently published technical rules for scoring large body movements in paediatric polysomnography to improve consistency.[60] The use of movement metrics has shown clinical utility. Stradling et al. reported greater movement in children with OSA than in controls, with improvement after adenotonsillectomy.[9,106] Coussens et al. used movement events as a marker of sleep fragmentation in paediatric OSA.[45] Traditional laboratory PSG uses multiple leads in an unfamiliar environment that can disturb sleep, whereas actigraphy, typically worn on the wrist or ankle, may miss full body movements. It is also unclear whether movement metrics can improve triage in the inconclusive McGill oximetry score 1 group (McGill 1–4: 1 = Normal or inconclusive, 2–4 = abnormal),[151,152] potentially reducing the need for unnecessary diagnostic PSG.

The Sonomat® is a mattress-based monitor with embedded sensors that detect body movements, snoring, and breath sounds. It has been validated for sleep-disordered breathing in adults, children, and in children with trisomy 21.[5-7] The Sonomat enables multi-night quantification of movement at home with minimal intrusion. Whether Sonomat-derived body movements can distinguish children with OSA from those without has not been evaluated. In resource-limited settings, combining movement data with oximetry may provide a more sensitive screening pathway than oximetry alone in the home setting.

We conducted a retrospective study of children who underwent concurrent in-lab video/PSG and Sonomat recordings for suspected sleep-disordered breathing. The primary objective was to compare movement metrics (MI and MD) between the two modalities with respiratory indices (MOAHI) also measured. We hypothesised that (1) children with OSA would exhibit higher movement indices than those without OSA and that (2) movement metrics could help classify children with a “normal/inconclusive” McGill oximetry score of 1, thereby improving the sensitivity of overnight oximetry screening. This is the first study to evaluate Sonomat movement metrics against video/PSG for OSA classification in children.

5.3 Methods

This was a retrospective cross-sectional analysis of a subset of children from a previously collected dataset who underwent paired in lab video/PSG and simultaneous Sonomat recording for OSA screening.[6] Exclusion criteria were primary non-respiratory sleep disorders, neurological conditions, and a requirement for respiratory support. Children were not screened or selected based on restless sleep. The analysed sample was restricted to studies with raw signals on both video/PSG and Sonomat of sufficient quality and with signals available for body movement scoring. Ethics approval was obtained from the Sydney Children's Hospital Network Human Research Ethics Committee (2021/ETH00839).

Polysomnography

Full in-lab PSG (with video) was performed using the ProFusion PSG5 (version 5.0, Compumedics, Melbourne, Australia). Recorded channels included EEG, electro-oculography (EOG), submental and bilateral tibialis anterior electromyography (EMG), electrocardiography (ECG), thoraco-abdominal respiratory inductance plethysmography, nasal airflow (pressure transducer and thermistor), snoring (tracheal microphone), pulse oximetry, transcutaneous CO_2, synchronised video and audio, and a body-position sensor. Sleep stages and respiratory events were scored according to American Academy of Sleep Medicine (AASM) paediatric criteria and absolute (continuous) sleep scoring[85] was applied to more accurately determine sleep and wake duration and to derive sleep-only and wake-only movement metrics. All other parameters were scored per AASM standards. Movements on video/PSG were scored using the criteria described in ***Table 1 from Chapter 4.*** No threshold was applied to the individual movement duration. Children were classified as having OSA when MOAHI ≥ 1/hr and as no OSA when MOAHI < 1/hr. The apnoea–hypopnoea index (AHI) and oxygen saturation nadir were also recorded.

Sonomat

The Sonomat (Sonomedical Pty Ltd, Balmain, NSW, Australia) is a mattress overlay with four embedded thermoplastic fluoropolymer (polyvinylidene difluoride; PVDF) sensors. Each sensor outputs a movement channel sampled at 250 Hz and a breath-sound channel sampled at 4 kHz. Two room microphones record ambient sound at the same 4 kHz sampling rate. During the time the video/PSG was acquired, the Sonomat was placed beneath the bedsheet under the patient. Data were analysed using Sonomat Replay software (V0.0.64.0, Sonomedical Pty Ltd, Balmain, NSW, Australia). MI and MD and respiratory parameters (AHI, MOAHI) were scored. Movements on the Sonomat were scored according to the criteria described in ***Table 1 from Chapter 4***. Movement duration was applied in the same way as to video/PSG. Total sleep period (TSP) was derived from video/PSG and defined as the interval from the first epoch of sleep to the last epoch of arousal before the end of the study. Times were synchronised with the Sonomat, and TSP was used as the denominator for movement indices. To avoid circularity in this movement focused analysis, we used the PSG-defined TSP as the denominator rather than the Sonomat's quiescent-time sleep estimate used by Norman et al in the original validation papers.[5]

Movement parameters

As the Sonomat has no EEG, movement indices used the PSG-derived TSP as the denominator.

The following movement parameters were calculated for both video/PSG and Sonomat:

- **Movement index (MI):** number of movement events per hour of TSP (events/hr).
- **Movement duration (MD):** cumulative time spent in movement expressed as a percentage of TSP (%).

Additional parameters from video/PSG

Sleep-only and wake sub-parameters were derived from video/PSG epochs using continuous sleep-epoch scoring. For sleep-only metrics, the denominator was **total sleep time (TST)**; for wake metrics, the denominator was **total wake time (TWT)**.

- **$MI_{sleep\text{-}only}$:** number of movements occurring during EEG-defined sleep per hour of TST (events/hr of TST).
- **$MD_{sleep\text{-}only}$:** cumulative duration of movements during EEG-defined sleep expressed as a percentage of TST.
- **MI_{wake}:** number of movements occurring during EEG-defined wake per hour of TWT (events/hr of TWT).
- **MD_{wake}:** cumulative duration of movements during EEG-defined wake expressed as a percentage of TWT.
- Mean or median individual movement duration during sleep and during wake.

Respiratory parameters

- AHI and MOAHI were scored per AASM paediatric recommendations using TST as the denominator. MOAHI was used to define OSA in this study.
- Saturation nadir

Sub-classification by McGill oximetry score

Overnight oximetry recorded during PSG was classified using the McGill score. As scores 2–4 typically indicate OSA, we prespecified analyses focusing on the normal/inconclusive group (score 1) to assess whether movement metrics could identify OSA within this subgroup. Within the McGill 1 group, children were further stratified by MOAHI (<1 vs ≥1) and movement parameters were compared between the groups with and without OSA.

5.4 Statistical analysis

Statistical and graphical analyses were performed using Jamovi (version 2.7.40) and GraphPad Prism (version 10.6.1 for macOS, GraphPad Software, Boston, Massachusetts USA). Movement index and duration were Log_{10} transformed prior to analysis to reduce skewness and stabilise variances for analysis in the residuals. Differences between children with and without OSA (MOAHI <1 vs ³1) were first examined using Mann-Whitney U on MI and MD. Movement index and movement duration was measured repeatedly within each child under two scoring methods (video/PSG and MAT). Linear mixed-effects models were fitted MI and MD as the outcome variable and scoring method and OSA status as fixed effects. A random intercept for subject was included to account for within-subject correlation of repeated measurements. Residual diagnostics were inspected for normality and constant variance and where assumptions were violated, outcomes were log_{10}-transformed. When Omnibus F-test was significant, we performed pairwise comparisons of estimated marginal means with Bonferroni adjustment for multiple testing. Associations between movement metrics and wake/sleep duration and MOAHI were assessed using Spearman's rank correlation coefficient. A p-value < 0.05 was considered statistically significant. Due to limited numbers of patients, video/PSG-only sub-metrics, and McGill's subgroup metrics are compared using the Mann-Whitney U test.

5.5 Results

The study included 36 children (21 male), with a median age of 5.9 years (IQR 3.0; range 2–12). BMI was recorded for 32 (89%) patients with a median of 17.2kg/m^2 (3.1; 14.3-37). ***Table 1*** summarises key video/PSG and movement parameters.

Table 1: *video/PSG and Movement Parameters*

N = 36 (21 Male, 15 Female)	**Median (IQR)**
Age (years)	5.9 (4.3-7.4)
BMI (kg/m^2) N =32	17.2 (15.7-18.8).
video/PSG Parameters	
AHI (n/hr)	1.8 (1.0-4.5)
MOAHI (n/hr)	0.9 (0.5-3.9)
SaO2 Nadir (%)	91 (88.8-93)
Total Awake Duration (min)	47.2 (72.8-97.1)
Total Sleep Duration (min)	437 (360.2-481.3)
Total Sleep Period (min)	498 (459.4-530.0)
Movement Parameters	
MI-MAT (n/hr)	36.9 (29.2-41.7)
MI-video/PSG (n/hr)	20.9 (18.1-27.0)
MD-MAT (% of TSP)	11.8 (8.0-18.3)
MD-video/PSG (% of TSP)	8.7 (5.9-14.6)
Median Individual Sleep Movement Duration (sec)	12.2 (10.2-14.2)
Median individual awake movement duration (sec)	19.0 (0.3-0.7)

Movement parameters by OSA status.

Seventeen children (47%) had MOAHI ≥ 1/hr and were classified as having OSA (median MOAHI 4/hr), the majority having mild OSA (MOAHI <5). The remaining 19 children comprised the no-OSA group (median MOAHI 0.5/hr). See ***Table 2***

Table 2: *Age, BMI, AHI and MOAHI by OSA status with Movement Parameters by OSA status and method.*

	No OSA (n=19) **Median (IQR)**	**OSA (n=17)** **Median (IQR)**	**P value** **Mann-Whitney U**
Age	5.0 (4.1-6.8)	5.8 (4.5-7.9)	0.47
BMI	17.3 (16.4-18.1)	17.0 (15.6-22.0)	0.93
AHI	1 (0.4-1.5)	4.8 (2.6-7.6)	<0.001
MOAHI	0.5 (0.2-0.7)	4.0 (1.8-7.0)	<0.001
MI-MAT	39.0 (31.6-41.2)	36.7 (29.3-43.5)	0.79
MI - video/PSG	20.7 (18.9-23.1)	24.8 (16.4-31.9)	1
MD-MAT	12.2 (8.1-19.2)	11.3 (8.1-17.6)	0.73
MD-video/PSG	8.8 (6.6-16.5)	8.7 (5.8-11.1)	0.34

No statistically significant differences were observed based on OSA status by either method (video/PSG or Sonomat) for movement parameters (MI or MD). See ***Table 2.***

For adjusted analyses, we modelled Log_{10} transformed MI and MD using a linear mixed-effects model with OSA status (MOAHI < 1 vs ≥ 1) and scoring method (MAT vs video/PSG) as fixed effects, and a random intercept for subject (36 children, 72 recordings). See ***Figure 1a&b***. The scoring method had a substantial effect on MI ($F(1,34) = 131.5$; $p <0.001$) and MD ($F(1,34) =36.4$; $p<0.001$), consistent with findings in chapter 5, while OSA status did not differ for MI ($F(1,34) = 0.07$; p 0.79) or MD ($F(1,34) =0.29$; $p=0.59$). The model showed good fit for both MI and MD (MI: marginal $R^2 = 0.31$; conditional $R^2 = 0.83$; MD: marginal $R^2 = 0.04$, conditional $R^2 = 0.93$). The very low marginal R^2 for MD suggest great between-child differences. After adjustment for methods, OSA status did not show a significant difference in either MI (b = -0.014, SE=0.05, 95% CI [-0.09- 0.11], t(34) = 0.27, p = 0.79) or MD (b = 0.04, SE=0.08, 95% CI [-0.21- 0.12], t(34) = 0.54, p = 0.59). (See supplement for further details of analyses). ***Table 3*** summarises the back transformed (original units) adjusted mean and mean difference, T statistic and Bonferroni p value for MI and MD by OSA status. See Supplement for the full analyses output.

Figure 1 a&b: Log_{10} (MI) and (MD) by OSA status and Method (video/PSG Vs MAT).

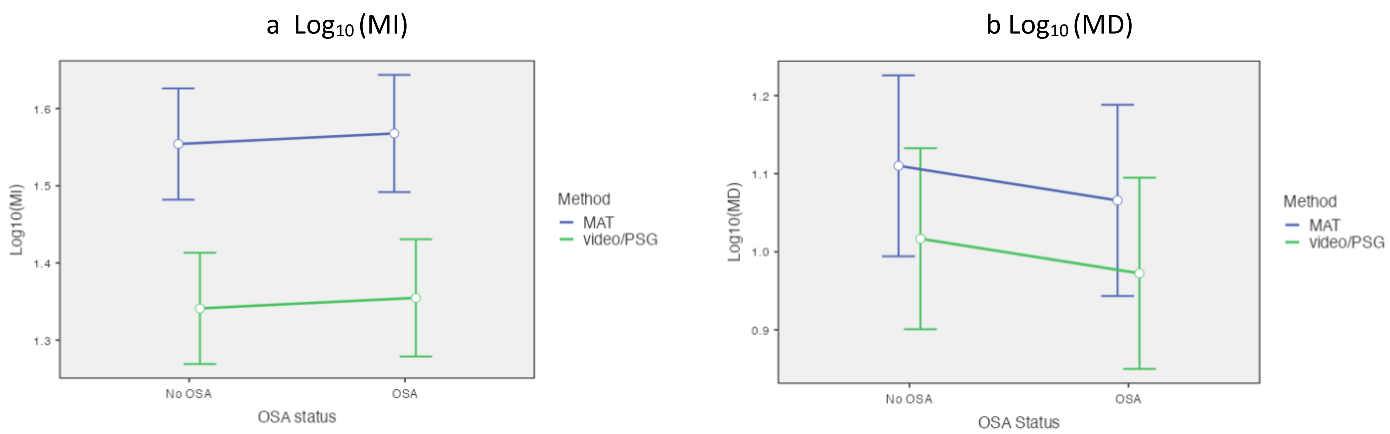


Table 3: MI and MD (back-transformed from Log_{10} MI and MD) by OSA status, adjusted for Method *

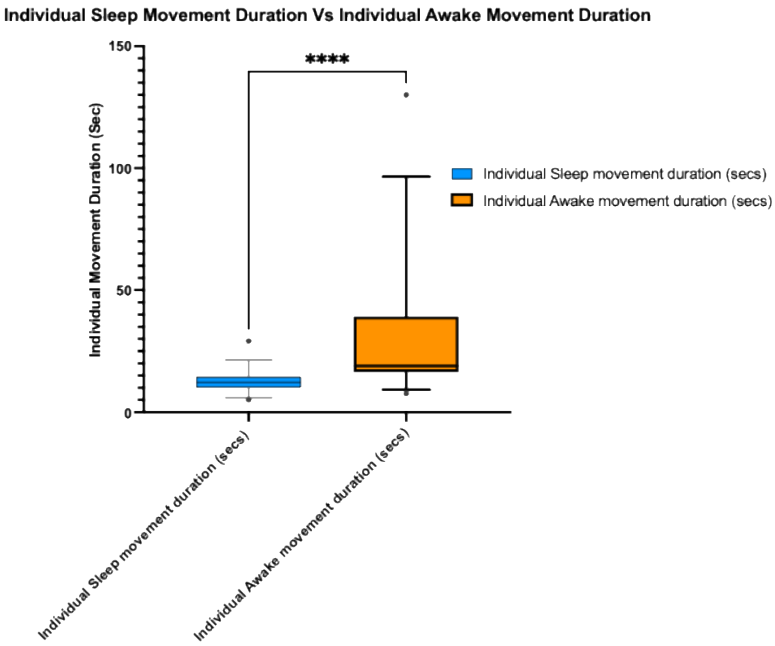
	No OSA, adjusted mean‡ (95%CI), units. n = 19	OSA, adjusted mean‡ (95%CI), units n = 17	Mean Difference Non OSA - OSA (95%CI)	t statistic	$p_{bonferroni}$
MI	28.2 events/hr (24.0-33.1)	28.8 events/hr (24.5-34.7)	-1.0 (-1.2-1.3)	-0.27	0.79
MD	11.5 % (8.9-15.1)	10.5 % (7.9-13.8)	1.1 (-1.6-1.3)	0.54	0.59

* From a linear mixed-effects model with log_{10}(MI) and log_{10}(MD) as the dependent variable, fixed effects for OSA status and method (video/PSG vs MAT) and a random intercept for subject (paired video/PSG/MAT per child).
‡ Estimated marginal means back-transformed from the log_{10} scale to the original MI and MD units,
§ p-value for the OSA status effect (OSA vs non-OSA) from the mixed model.

Sleep-Only Movement Parameters

Participants slept a median of 437 min and were awake for 47.2 min by PSG-defined EEG staging. When movements were stratified by PSG-defined sleep and wake, the median movement duration was 12.2 sec (IQR 4.32) during sleep versus 18.9 sec (IQR 24.4) during wake, indicating significantly longer individual movements during wakefulness (Wilcoxon signed-rank, $p < 0.001$) as illustrated in ***Figure 2.***

Figure 2 *Box plot of Individual movement duration Sleep Vs Wake*



Correlation of movement metrics with wake and sleep duration

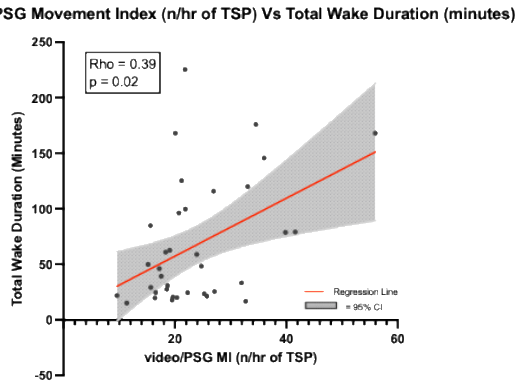
Both video/PSG and Sonomat (MAT) movement metrics were related to time awake (after sleep onset). On video/PSG, MI correlated moderately with total awake duration (Spearman ρ = 0.39, p = 0.020), and MD correlated very strongly (ρ = 0.90, p < 0.001). For the Sonomat, MI also correlated moderately with total awake duration (ρ = 0.41, p = 0.014), and MD also showed a strong association (ρ = 0.83, p < 0.001) as demonstrated in ***Figure 3 a&b***.

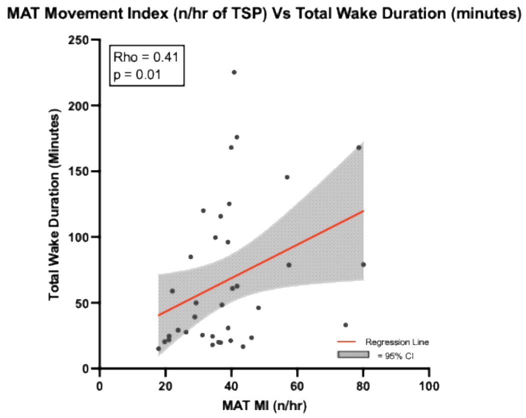
Correlation between Movement metrics with Wake duration: video/PSG and Sonomat (MAT)

a. video/PSG Movement Parameter vs Total Wake duration (after sleep onset)

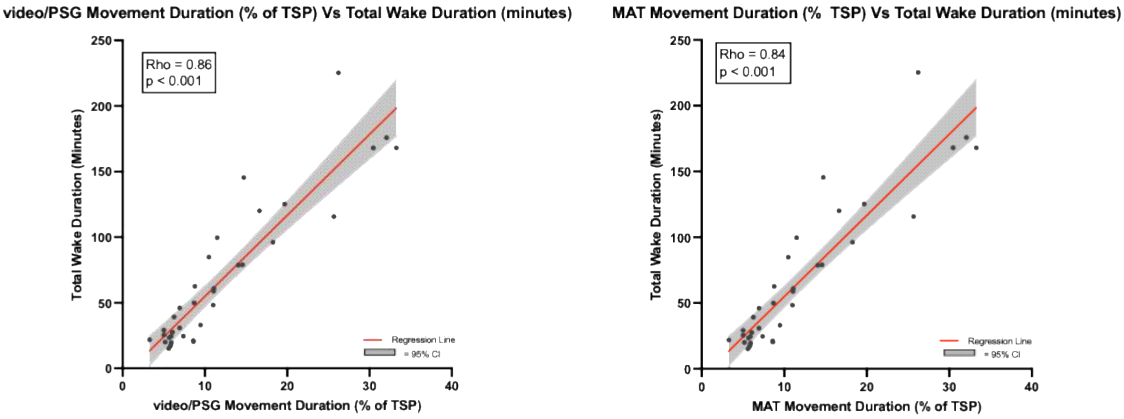
b. MAT Movement Parameter vs Total Wake duration

Movement Index





Movement Duration

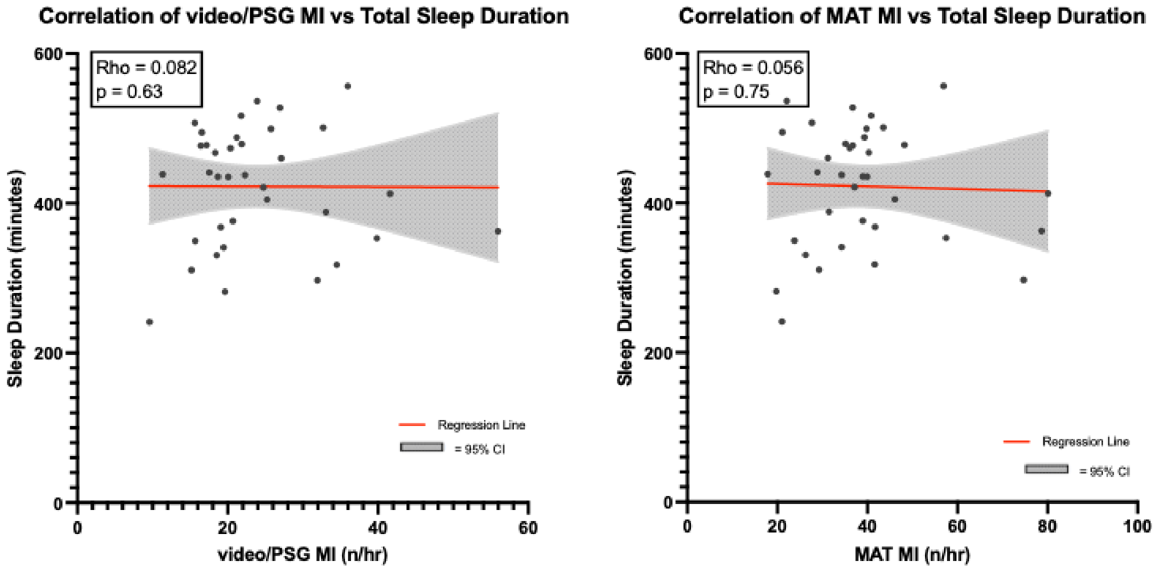


In contrast, MI and MD showed no significant relationship with total sleep duration (video/PSG MI ρ = 0.082, p = 0.63; Sonomat MI ρ = 0.056, p = 0.75; video/PSG MD ρ = 0.14, p < 43; Sonomat MD ρ = 0.1, p = 0.56). See ***Figure 4a&b***

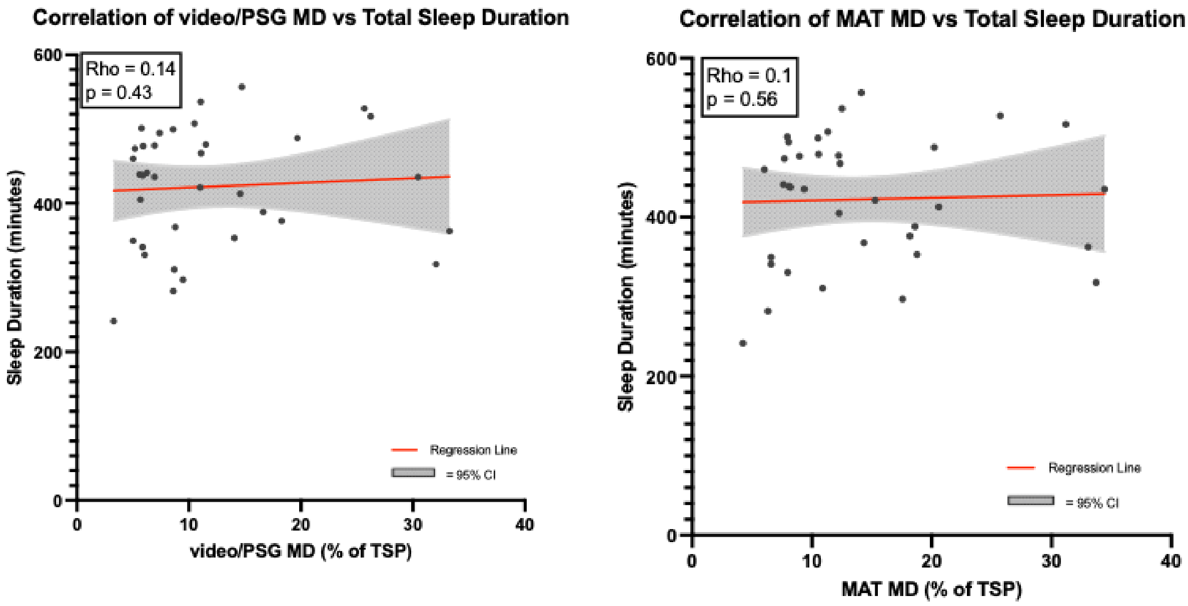
Figure 4a&b: *Correlation between Movement metrics with Sleep duration: video/PSG and Sonomat*

Figure 4 | *a. video/PSG Movement Parameter vs Total Sleep duration* | *b. MAT Movement Parameter vs Total Sleep duration*

Movement Index



Movement Duration



Sleep only Movement parameters by OSA status

Given the significant impact of wake time on movement, sleep-only movement parameters were reviewed by OSA status. Due to small numbers in the cohort, a Mann-Whitney U test was performed which showed no difference between MI or MD by OSA status. See ***Figure 5a&b*** and ***Table 4***.

Figure 5 a&b: Sleep Only Movement Index and Movement Duration by OSA Status

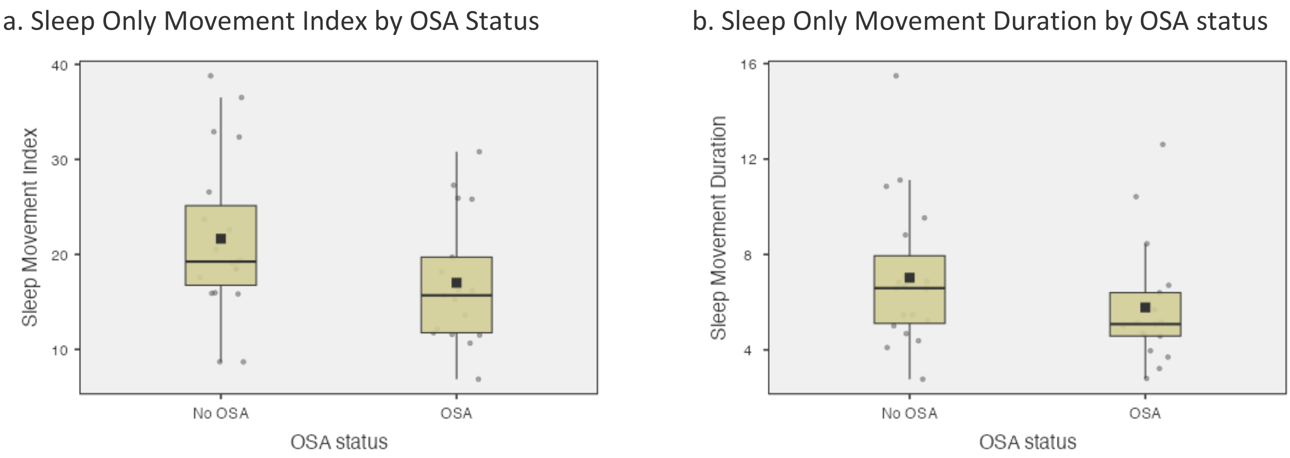
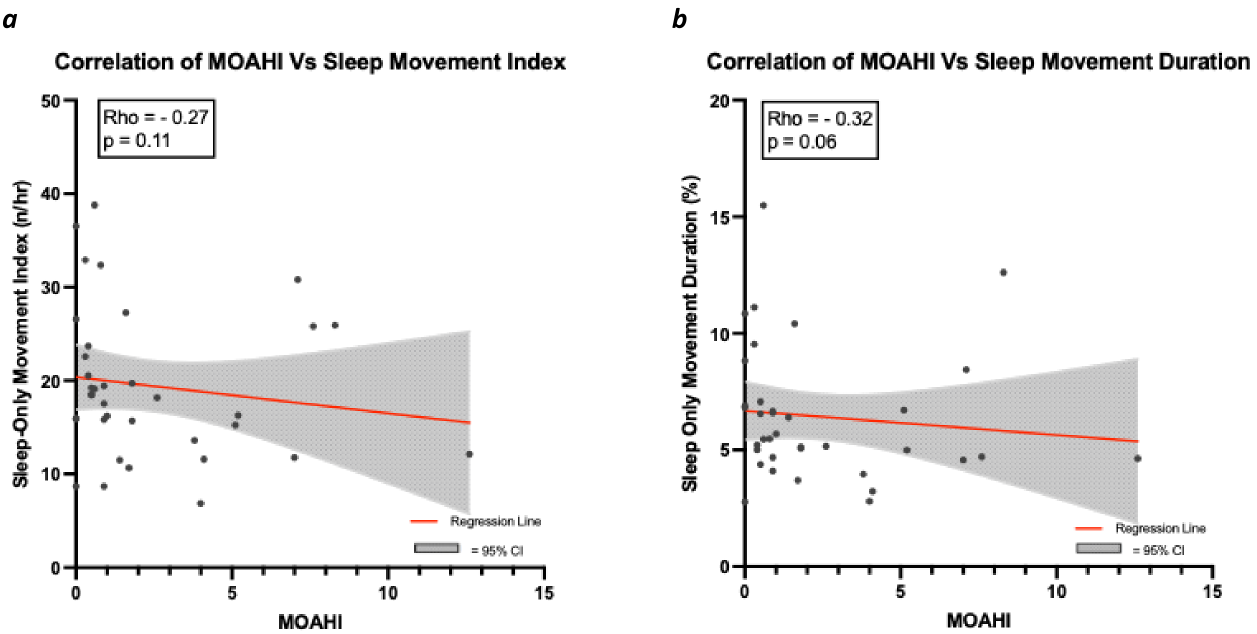


Table 4: Sleep Only Movement Parameters by OSA Status

	NO OSA N=19 Median, IQR	OSA N=17 Median, IQR	Mean difference (95% CI)	U stat	P value	Effect size Rank biserial correlation
MI	19.2 (16.8-25.1)	15.7 (11.8-19.7)	4.4 (-0.3 – 8.5)	101	0.057	-0.37
MD	6.6 (5.1-8.0)	5.1 (4.6-6.4)	1.2 (-0.2 – 2.4)	108	0.093	-0.33

There is a weak correlation between the MOAHI and Movement parameters measured during sleep only. $MI_{sleeponly}$ (rho -0.27, p =0.11) and $MD_{sleeponly}$ (rho – 0.32, p = 0.06) ***Figure 6a&b***

Figure 6a&b *Correlation between MOAHI and Sleep Movement Index and Sleep Movement duration*



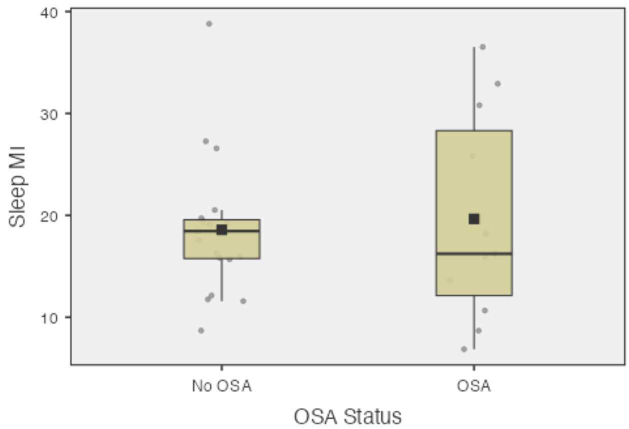
Sub-analysis of the McGill score 1 subgroup

Thirty of 36 children (83%) had McGill score 1 ("inconclusive") on overnight oximetry; 11 had OSA (MOAHI ≥ 1/hr) and 19 had no OSA (MOAHI < 1/hr). Within this subgroup, sleep-only movement metrics did not discriminate OSA status. See ***Figure 7a&b*** and ***Table 5***.

Figure 7a&b Movement Index and Movement Duration by OSA status MAT and video/PSG.

a

McGill Score 1: Sleep-Only MI by OSA status



b

McGill Score 1: Sleep-Only MD by OSA status

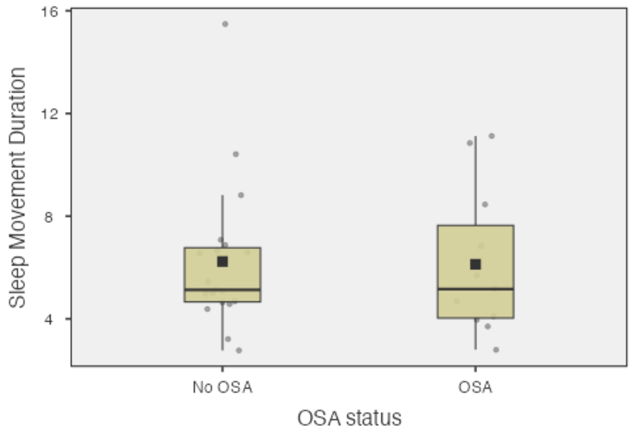


Table 5: McGill Score 1 Group: Movement Parameters by OSA Status

	NO OSA N=19 Median, IQR	OSA N=11 Median, IQR	Mean difference (95% CI)	U stat	P value	Effect size Rank biserial correlation
MI	18.6 (15.8-19.6)	19.7, (12.1-28.3)	0.9 (-9.3 – 5.8)	97	0.77	0.072
MD	5.1 (4.7-6.8)	5.2 (4.0-7.6)	0.3 (-1.8 – 1.9)	100	0.87	0.043

5.6 Discussion

This study examined whether objective metrics of gross body movements, recorded concurrently by video/PSG and the Sonomat, could discriminate the presence of (mild) paediatric obstructive sleep apnoea. Children showed markedly longer movement episodes during wakefulness than during sleep, and movement indices increased with total wake time. Despite restless sleep being a recognised feature of paediatric OSA and a recommended trigger for screening by international sleep associations,[153] gross body-movement metrics did not distinguish children with (mostly mild) OSA from those without OSA in our cohort of patients. In children with inconclusive oximetry, gross body movements on the Sonomat did not improve OSA classification.

Implications for interpretation of movement metrics

The movement indices recorded in this study were higher than those reported in prior paediatric studies because we quantified movements across the TSP to allow direct comparison between Sonomat (no EEG) and video/PSG. Using TSP as the denominator included wake periods after sleep onset but within the recording window, which inflates indices relative to analyses restricted to EEG-defined sleep (TST). Results should therefore not be compared directly with literature that reports PSG-based, sleep-only metrics.

In PSG-specific analyses that separated sleep from awake state, movement measures tracked wakefulness. Children's movements were longer when awake than during sleep, and both MI and MD increased with time awake. These findings are consistent with findings from Actigraphy where mean activity levels were significantly higher during wakefulness than during sleep (25.87 counts vs 6.84 counts).[30] These findings also suggest that mattress-based gross-movement signals primarily index wake-related activity and support developing a movement-based algorithm to classify time asleep versus wake on the Sonomat in children as was developed for adults.[26]

In addition, although both MI and MD tracked wakefulness after sleep onset, the correlation was much stronger for MD. This highlights a potential measurement issue: MI is sensitive to event segmentation (for example, one prolonged movement versus two shorter movements), whereas MD is less affected and thus is likely to be more reproducible across scorers and devices.

When restricted to sleep-only epochs on video/PSG, movement metrics did not differ between non-OSA and OSA, in contrast to Stradling's findings.[106] Stradling's methodology relied on detecting light changes from video recordings, which may miss many movements that were captured by video/PSG in our study. Interpretation is limited by the absence of selection for restless sleep, therefore, other potential drivers such as RSD, PLMS, may have been present.

In our cohort, MD was higher in the non-OSA group for both the overall and the sleep-only analyses. By contrast, MI overall was lower in the non-OSA group than in the OSA group, a direction that differed from Sleep-Only comparison. This underscores the impact of the chosen denominator on effect estimates as well as the measurement issue highlighted above. This distinction is important considering prior validation work. Norman et al. (2017) showed that calculating respiratory indices based a Sonomat-derived surrogate TST (quiescent time–based) yielded values comparable to PSG.[26] As movement influences quiescent-time estimates, using this denominator would introduce circularity in our movement-focused analysis. Therefore, we calculated respiratory indices to PSG-defined TST and movement metrics to PSG-derived TSP as well as sleep-only (TST) metrics respectively.

Potential confounders not captured in our dataset include unmeasured snoring or stertor as a marker of partial upper-airway obstruction. The Sonomat records respiratory signals that were not analysed in this study. Norman et al. showed that the device quantifies prolonged snoring and stertor, markers of partial obstruction, at rates an order of magnitude higher than discrete apnoeas and hypopnoeas, suggesting that indices based on snore/stertor duration may better reflect sleep-disordered-breathing severity than AHI alone.[6] In the context of no association between movement metrics and MOAHI, unmeasured snoring may have contributed to the lack of movement signal. Future studies should quantify snoring and stertor and examine its relationship with MI and MD.

Given that our primary analyses considered all movements (i.e. no minimum threshold applied to individual movement duration) and from previous analyses (chapter 4), movement metrics depend on event duration thresholds, group comparisons may vary if changes were made in the movement threshold.

Interpretation considering previous literature

Stradling et al. quantified sleep disturbance from overnight video as the percentage of time spent moving, excluding prolonged wakefulness.[106] Snoring children moved more than controls (median ~8.8% vs ~5%), falling to ~5.8% six months after adenotonsillectomy.[9] Our median MD values (~10.5% on Sonomat; 10.8% on video/PSG) are higher, likely reflecting our lower event threshold (movements of any duration) and the use of TSP rather than sleep-only time as the denominator. These contrasts underscore how movement definitions and denominators shape estimates and support the need for device-specific normative ranges.

Norman et al also found that respiratory event induced movements decreased from 12 to 0.5 following surgery, with no significant change in spontaneous movements. [73] Obstructed breathing runs continued to be associated with respiratory movements post-surgery. Their study found that when obstructed breathing was objectively measured, there was a large variation in children's response to surgery.

Coussens et al. modelled 'sleep runs' defined as continuous sleep terminated by movement and derived an exponent (θ) from Kaplan–Meier curves.[45] The θ separated OSAS from primary snorers and controls at baseline and after adenotonsillectomy, whereas conventional metrics (R&K movement time, stage 1 sleep, awakenings) did not. Our MD metrics likewise did not separate groups. Therefore, it may be better to assess distribution-based analyses of movement rather than simple counts or totals. Note that Coussens movement-time metric followed R&K rules, which are coarse: any 30-s epoch with >50% movement is labelled "movement," whereas our study used continuous scoring with shorter event duration thresholds.

McGill score 1 (normal/inconclusive) subgroup.

A large proportion of screened children fall into McGill score 1, and roughly half of these are diagnosed with OSA on subsequent PSG.[151] We tested whether gross body-movement metrics from video/PSG or the Sonomat could improve triage within this group and found no discrimination between children with and without OSA. This suggests that movement burden, when used alone, adds little to oximetry for inconclusive studies. Bertoni et al. combined oximetry with actigraphy in machine-learning models and reported high performance for AHI >10 (95–96%) and >2 (87–89%).[154] As they did not stratify by McGill score and used Machine learning derived features, applicability of their results to our McGill-1 subgroup and to simple movement metrics (MI, MD) is limited.

Strengths and limitations

The strengths of this study include simultaneous, synchronised video/PSG and Sonomat recordings, enabling direct modality comparison and calculation of sleep-specific movement metrics in a typical tertiary referral cohort.

Limitations of this study include the retrospective design and modest sample size, which reduced power. The referral nature of the cohort means there were no true controls as most children were snorers, which may limit generalisability and impact the true difference in comparison between OSA vs normal cohort. Most subjects included had mild OSA and potentially greater numbers with a broader range of OSA severity may have yielded different results.

As the Sonomat has no EEG, overall movement indices were calculated based on the total sleep period rather than EEG-confirmed TST, potentially diluting sleep-specific effects. We did not exclude other movement disorders (e.g., periodic limb movements or restless legs), which could increase movement independent of respiration. Parent-reports of restlessness and daytime symptoms were not collected, preventing comparison of objective metrics with subjective outcomes.

We also did not quantify partial upper airway obstruction (snoring or stertor), a common feature in children with SDB. Our primary analysis considered all movements and we did not evaluate different duration thresholds. Sensitivity analyses with higher cut offs (e.g. ≥1s, ≥3s, ≥5s) could clarify whether between group differences exist in larger movements, which may be obscured by numerous short events, although this is largely addressed by the movement duration metric. This should be explored in future work.

Clinical Implications and Future directions

For children with OSA and those with inconclusive oximetry (McGill 1), gross body-movement metrics derived from either video/PSG or Sonomat did not discriminate those with vs without paediatric OSA. Movement burden closely tracked wakefulness after sleep onset. Applying movement characteristics to classify sleep–wake states on the Sonomat may improve the specificity of movement indices. Given the contribution of partial upper-airway obstruction (snoring/stertor) in paediatric sleep disordered breathing, future work should test whether specific movement patterns co-vary with these signals. Distribution-based analyses (e.g. inter-movement intervals) may also be more informative than crude counts or total duration as demonstrated by Coussens et al.

This was among the first studies to examine movement parameters with video/PSG and Sonomat. The modest sample size limited statistical power, and a true healthy control cohort was not included. Larger controlled cohorts, combined with multi-night home recordings, are required to define normative ranges, capture night-to-night variability, and clarify whether high movement predicts daytime symptoms.

5.7 Conclusion

In this retrospective analysis of 36 children with concurrent video/PSG and Sonomat recordings, gross body movements were strongly linked to wakeful periods after sleep onset. Movement metrics did not differ between non-OSA and OSA groups nor did they help resolve inconclusive oximetry defined by MOAHI. Further work should apply sensitivity testing at other individual movement duration thresholds and evaluate whether movement metrics differ according to the presence and burden of snoring and stertor, features of sleep disordered breathing that are measurable on the Sonomat recordings but are not captured by the MOAHI.

5.8 Supplementary to Chapter 5: Sleep Movements And Obstructive Sleep Apnoea In Children Assessed By Sonomat And Polysomnography.

Supp Table 1: Linear Mixed Model Log_{10} MI by OSA status and Scoring method. (Jamovi Output).

Fixed Effects Omnibus Tests

	F	df	df (res)	p
OSA status	0.0746	1	34.0	0.786
Method	131.5499	1	35.0	2.09e-13

Parameter Estimates (Fixed coefficients)

				95% Confidence Intervals				
Names	**Effect**	**Estimate**	**SE**	**Lower**	**Upper**	**df**	**t**	**p**
(Intercept)	(Intercept)	1.4544	0.0250	1.4045	1.504	34.0	58.131	1.28e-35
OSA status1	OSA - No OSA	0.0137	0.0500	-0.0862	0.114	34.0	0.273	0.786
Method1	video/PSG - MAT	-0.2130	0.0186	-0.2500	-0.176	35.0	-11.470	2.09e-13

Estimate Marginal Means - OSA status

				95% Confidence Intervals	
OSA status	**Mean**	**SE**	**df**	**Lower**	**Upper**
No OSA	1.45	0.0344	34.0	1.38	1.52
OSA	1.46	0.0364	34.0	1.39	1.54

Estimate Marginal Means - Method

				95% Confidence Intervals	
Method	**Mean**	**SE**	**df**	**Lower**	**Upper**
MAT	1.56	0.0267	43.2	1.51	1.61
video/PSG	1.35	0.0267	43.2	1.29	1.40

Supp Table 2: Linear Mixed Model Log_{10} MD by OSA status and Scoring method. (Jamovi Output).

Fixed Effects Omnibus Tests

	F	df	df (res)	p
Method	36.441	1	35.0	6.91e-7
OSA Status	0.290	1	34.0	0.594

Parameter Estimates (Fixed coefficients)

				95% Confidence Intervals				
Names	**Effect**	**Estimate**	**SE**	**Lower**	**Upper**	**df**	**t**	**p**
(Intercept)	(Intercept)	1.0413	0.0412	0.959	1.1234	34.0	25.294	1.24e-23
Method1	video/PSG - MAT	-0.0933	0.0155	-0.124	-0.0625	35.0	-6.037	6.91e0-7
OSA Status1	OSA - No OSA	-0.0443	0.0823	-0.209	0.1200	34.0	-0.538	0.594

Estimate Marginal Means - Method

				95% Confidence Intervals	
Method	**Mean**	**SE**	**df**	**Lower**	**Upper**
MAT	1.088	0.0419	36.4	1.003	1.17
video/PSG	0.995	0.0419	36.4	0.910	1.08

Estimate Marginal Means - OSA Status

				95% Confidence Intervals	
OSA Status	**Mean**	**SE**	**df**	**Lower**	**Upper**
No OSA	1.06	0.0566	34.0	0.948	1.18
OSA	1.02	0.0598	34.0	0.898	1.14

Chapter 6: Synthesis, Conclusions and Future Directions

6.1 Chapter Overview

This chapter integrates the findings across Chapters 2-5.

6.2 Measuring Body Movements with Sonomat

Sonomat detects more brief movements than video/PSG Across all events (no duration threshold), Sonomat registers more movements and greater cumulative movement time than video/PSG. Discrepancies concentrate in short events.

- ***Convergence emerges for longer events***

When filtering to individual movement duration ≥ 7 s, Sonomat and video/PSG converge: device differences shrink and agreement on MI/MD improves. This supports using ≥ 7 s for cross modality comparisons while retaining the full, no threshold view for descriptive completeness.

- ***Movement Duration is the preferred burden metric***

MD is less sensitive to event-splitting or merging than MI. If two brief movements are scored as one (or vice-versa), MI changes but MD is comparatively stable. MD should be the primary movement burden indicator while MI is supportive and useful for distributional description, with more studies required to determine any correlations with other clinical outcomes.

- ***Automation behaves asymmetrically***

On the Sonomat, the intrinsic automated scoring (Sonoauto) approximates manual scoring for MD but not for MI. MI was poor across all automated scoring methods against manual scoring. MD is the more automation-ready endpoint.

6.3 Clinical Interpretation

- ***Movement Burden tracks wakefulness***

Overnight movement time correlates with PSG-derived wake time. Parental reports of 'restlessness' may reflect greater wakefulness rather than movement confined to sleep. Based on our cohort, movement burden is best interpreted as a marker of sleep continuity, not a disorder specific signature. By contrast, video-PSG evidence from DelRosso et al shows higher large body movements (measured by video only) during sleep in children with restless sleep than controls, indicating disorder-specific elevation in that cohort.[24]

- ***No discrimination for OSA in this cohort***

Using the thesis definitions (TSP denominator; MI events/hr; MD %), movement parameters did not differentiate OSA vs non-OSA (based on MOAHI diagnosis) and did not add value within McGill score of 1. The sample comprises children referred for suspected SDB and habitual snoring with no asymptomatic control group (either true community controls or follow-up after treatment). Without this 'normal', between group contrasts are limited. This limits generalisability for discrimination claims but does not diminish inferences about device comparability and metric behaviour. Movement may accompany partial airway obstruction (e.g. snoring, stertor) without meeting OSA thresholds, but this was not explored in this thesis and warrants further investigation.

6.4 Limitations

The design used single-night, lab studies with quality selected records in a cohort of children referred for snoring. Scoring was device specific and blinded, without cross modal confirmation. Apparent unilateral events may reflect true device differences or modality specific artefact. Using PSG defined TSP as a common denominator allowed standardisation of the time base across devices however, because Sonomat cannot differentiate sleep from wake, true sleep only movement measurement was not possible on the Sonomat recordings alone. The absence of EEG on Sonomat means increased movement may simply reflect increased wake, limiting sleep-only inference without EEG from PSG. We found that agreement was more robust for individual movement durations ≥ 7 s. Shorter thresholds exaggerated device differences, likely due to greater Sonomat sensitivity and event splitting and merging. The retrospective design and limited sample size meant the study was underpowered for more than simple, unadjusted, univariate subgroup comparisons.

Both studies in this thesis required complete raw files and adequate signal quality for inclusion. This may have introduced selection bias towards children with more stable recordings and lower movement burden, as technically compromised studies, which may have been associated with greater movement activity, were excluded. As a result, the findings may be less generalisable to children with poorer signal quality or higher movement burden. Future prospective studies should aim to reduce this limitation through improved recording protocols.

6.5 Future Work

Partial-obstruction metrics for analysis of SDB
Future work should quantify partial upper-airway obstruction using audio and respiratory measures (snore, stertor) presence and rate and model these alongside Movement duration (primary) and MI (secondary) to assess sleep continuity and to test whether obstructive breathing time correlates with MD. Sensitivity testing at different event thresholds will also be valuable.

Movement microstructure and sleep-wake differentiation on Sonomat
Differentiating sleep from wake on Sonomat to accurately detect movements during sleep is essential. We will model the temporal structure of movement by exploring inter-movement intervals distributions, run lengths and transition rates to help build a model to classify wake versus sleep on the Sonomat for children. This will be validated against PSG-defined sleep and wake in this cohort.

Multi-night home cohorts and normative data.
Future work should also evaluate multi-night home Sonomat recordings to quantify night to night variability and enable large population studies to derive age and sex specific normative reference ranges for movement metrics.

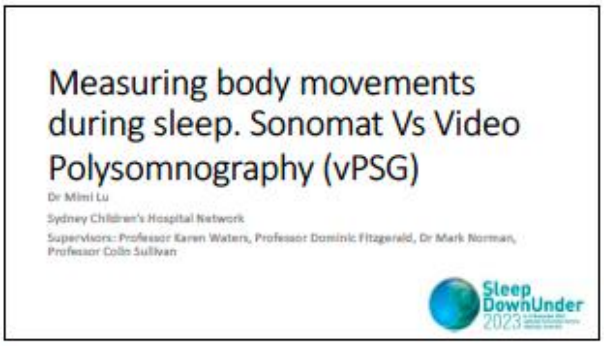
Automation
Automated MD estimation should be developed and validated for routine use and establish test-retest benchmark datasets to support external validation and reproducibility.

6.6 Conclusion

The Sonomat detected more brief movements than video/PSG, but modalities converged for events ≥ 7 s. Movement Duration was the more robust summary metric whereas MI can be labile to scoring variations. Automated Sonomat scoring performed comparably to manual scoring for MD. Movement burden aligns with wake time rather than OSA status in our cohort.

Appendix

Slides from Oral presentation at Sleep Down Under 2023.



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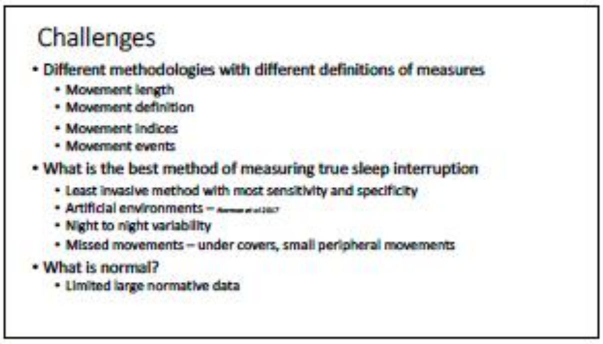

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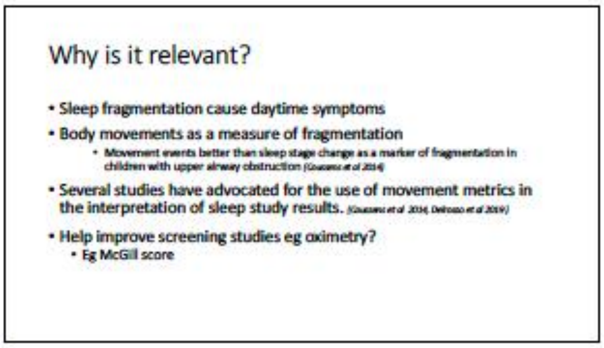

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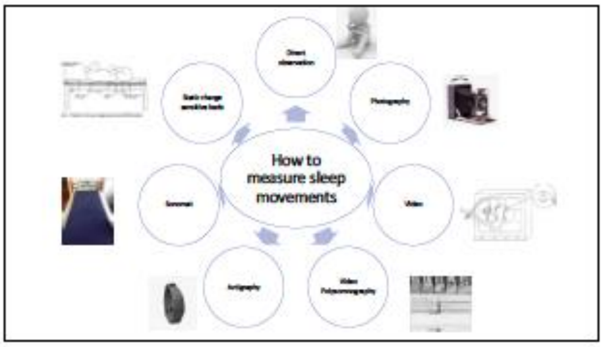

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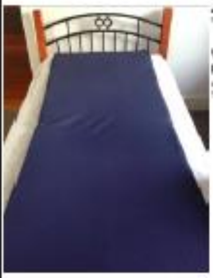
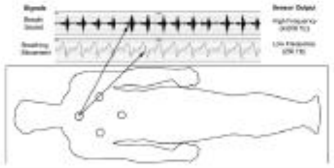
Sonomat



Validation of the Sonomat: A Contactless Monitoring System Used for the Diagnosis of Sleep Disordered Breathing

Validation of the Sonomat Against PSG and Quantitative Measurement of Partial Upper Airway Obstruction in Children With Sleep-Disordered Breathing



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Aim

- Compare body movements measured by the Sonomat with those recorded using video PSG
- Hypothesis: Sonomat is as capable as vPSG in it's ability to detect body movements during sleep.
- *Sonomat is a better device at measuring true sleep disruption.*

8

Methods

- Retrospective study *(Validation of the Sonomat against PSG and quantitative measurement of partial upper airway obstruction in children with sleep disordered breathing. Norman et al 2017)*
- Concurrent studies using Sonomat and vPSG
- Blinded scoring of movements using Sonomat and vPSG on separate days
- Measurements
  - Movement duration (total duration of movements as % sleep period time)
  - Movement index (number of movements /hour of sleep period)
  - *Sleep period: time between first recorded epoch of sleep and the last recorded epoch of sleep*
- Statistical analysis
  - Wilcoxon rank test on paired data
  - Mann Whitney U test on unpaired data
  - $P < 0.05$ statistical significance

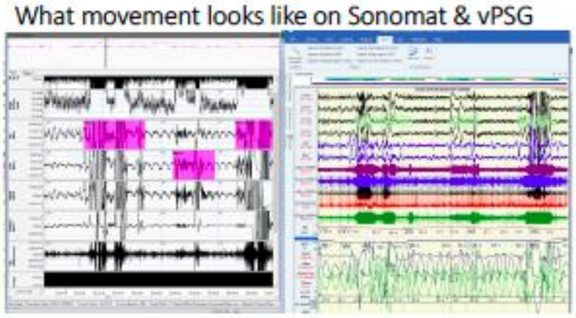
9

Results

- N = 29
- Median age 5.4 years (IQR 3.5, Range 2-12.4 years)
- 13 Females, 16 Males
- Sleep period – median 499 minutes (IQR 70.7, Range 388-588)

10

What movement looks like on Sonomat & vPSG



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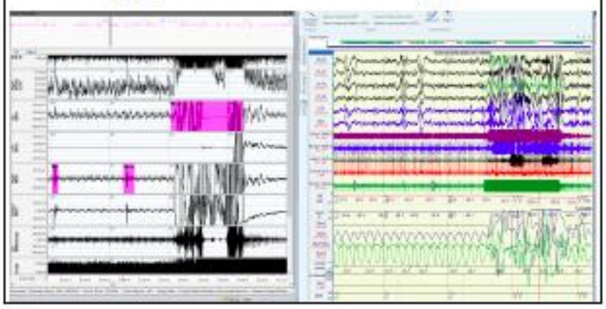
Sonomat vPSG



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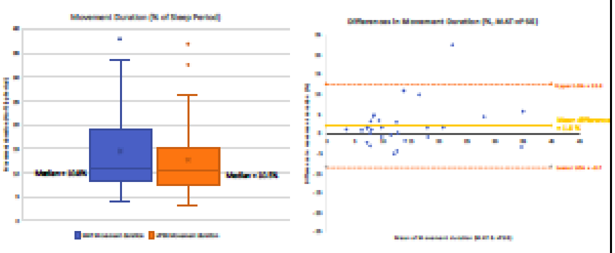
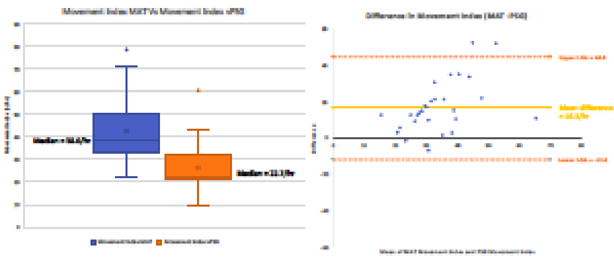
Results: Movement Duration (total movement duration/Sleep Period, %)



P = 0.08

13

Results: Movement Index (number of movements/hr of Sleep Period)



P< 0.001

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Movement Index (by thresholds)	Mean Difference in Movement Index (n/hr) (MAT– PSG)	P value (Wilcoxon signed rank test)
Movement >1 second = M1	16.3	<0.001
Movement >3 seconds = M3	6.9	0.004
Movement >5 seconds = M5	3.2	0.05
Movement >7 seconds = M7	1.6	0.183

- For movements greater than 7 seconds – The Sonomat is as good as vPSG at picking up the number of movements
- Sonomat detects more short duration movements
  - *Movements during sleep tend to be shorter than awake movements (mean difference 1.27 minutes, W=68, p <0.001) unpublished data*
  - *Correlation of movements with Arousals R=0.49, p = 0.007, unpublished data*
  - *Small movements (eg PLMS) can be associated with sleep disturbances and daytime behavioural problems (Stagno et al 2011, Gaultney et al 2009)*

15

Movements > 1 second

- Sonomat identified 82.5% of the movements seen on vPSG
- vPSG identified 43.6% of those seen on Sonomat, increased to 64.4% if matched for movement duration.

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Limitations

- Retrospective
- Small sample size
- Symptomatic population (snoring children, OSA and non OSA)
- No specific restlessness history

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Conclusion

- The Sonomat is better at detecting shorter body movements compared to vPSG.
- The Sonomat offers a promising alternative for assessment of sleep movements (indirect measure of restlessness) in children.
- Future directions
  - Normal cohorts
  - Adjunct to screening tests
  - Assess true sleep interruption as an impact of disease
    - The system has less impact on child than PSG, better assessment on the true impact on sleep

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