Supplementary Material - Feasibility and exploration of remote multimodal sleep measurement in autistic and nonautistic smartphone users

Tables

Table S1. Summary of eligibility criteria and other characteristics varying across enrolment sources

	Longitudinal European Autism Project	Additional non autistic sample
N enrolled	48 total 34 autistic 14 non autistic	26 total 0 autistic 26 non autistic
Clinical characteristics	Autistic and non autistic	No known or suspected neurodevelopmental, neurological, mental health or sleep conditions
Age	12 years or older	20-30 years (inclusive)
Smartphone ownership	Original: independent user of an Android smartphone (version 8 or later) due to pRMT compatibility Revised: iPhone users were later invited to maximise sample size within LEAP	Independent user of an Android smartphone (version 9 or later)
Fitbit model	Inspire 2	Inspire 3 (Inspire 2 discontinued)

Table S2. Smartphone sensor data used in this study

Sensor	Description	Consideration	Indicators of activity
Smartphone Accelerometer	Acceleration (in m/s^2) along the resultant of x, y, and z axes.	Phone must be used by the participant; phone placement affects accuracy.	3% change in average resultant acceleration value in successive 2-second time windows.
Smartphone Light Sensor	Ambient light level in lux captured by phone's front-side sensor.	Screen light, phone orientation, placement, or covers may affect accuracy.	Drop of 10 or higher averaged lux value in successive 60-second time windows.
Smartphone App Usage	Logs of app foreground and interaction activity with timestamps.	Background tasks and notifications not captured.	Logs of foreground or interaction app event.
Fitbit Steps	Count of steps recorded by Fitbit wearables.	Devices must be worn properly.	Logs of steps taken by the participant.
Fitbit Sleep Stages	Labels of sleep stages (light, deep, REM, awake) with timestamps and durations.	Overlapping stages, ambiguity between two sleep detection algorithms of Fitbit can affect accuracy.	Stage labelled as 'AWAKE'.

Table S3: Steps involved in extracting passively derived sleep features

1. Identify daily **Primary Sleep Period (PSP)** and derive **Sleep onset** and **Sleep offset times**.	(A) Consecutive sleep stages were grouped into a single sleep session if the time gap between the end of one sleep stage and the start of the next was less than 180 minutes. A gap greater than 180 minutes between consecutive sleep stages is considered as an extended period of wakefulness. Upon observing such a period, a

	new sleep session is defined. This allowed to distinguish multiple periods sleep throughout the day (e.g., overnight sleep from naps).
	(B) (i) Sleep sessions whose durations were outside the range of 120-720 minutes, were discarded. (ii) The range of 120-720 minutes was used to remove outliers of TST.
	(B) Each sleep session was assigned a wake-up date based on the calendar date of the final timestamp in the session. This corresponds to the time the participant woke up from that sleep session.
	(C) If multiple sleep sessions occurred with the same wake-up date, the session with the longest TST was retained as the PSP for that day. The start and end times of the PSP were used as the participant's **sleep onset time** and **sleep offset time**, respectively and these times were assigned to the calendar date the participant woke up.
2. Derive instances of passive awake markers before daily PSP: (A) **Phone pick up** (B) **Lights off** (C) **Active phone usage** (D) **Steps taken**	(A) Derive **phone pick-up** instances using changes in smartphone accelerometer data. (i) Calculate the resultant acceleration value $\sqrt{x^2 + y^2 + z^2}$ where x , y , and z represent the acceleration values along those axes. (ii) Multiple smartphones were tested by ringing on vibration mode and by barely picking it up to account for definite phone pick-up instances. A 3% change in average resultant acceleration value in successive 2-second time windows was considered as the threshold to mark the later window as a wakeful phone pick-up instance.

	(B) Derive **lights off** instances using change in ambient light sensor data. (i) After testing with multiple smartphones in different lighting conditions, a drop of 10 or higher averaged lux value in successive 60-second time windows, where the average lux value of the later time window is less than 18, was considered as a light turn-off instance. (iii) The start time of the later window is selected as the lights turn-off instance.
	(C) Derive instances of **active phone usage** from app usage logs and screen state events timestamps. Active phone usage state was defined as periods when the phone was unlocked, overlapping with foreground or interaction app activity timestamps.
	(D) **Steps taken** instances were derived from Fitbit step count timestamps where the number of steps taken were higher than zero.
	(E) Group all four instances from steps (A) – (D) as **awake marker instances**.
3. Calculate **Sleep Preparation Period (SPP)**	(A) Identify the closest preceding awake marker timestamp for each of the daily sleep onset time.
	(B) If the time difference between the sleep onset time and its closest preceding awake marker is less than 120 minutes, then the time difference is taken as the **SPP**. Otherwise, it is marked as N/A.
4. Calculate **latency to arising** Latency to arising is the time difference between waking up and getting up from bed.	(A) Identify the closest succeeding instance of **steps taken** after **sleep offset time** using Fitbit steps data.
	(B) The time difference between **sleep offset time** and its closest succeeding **steps taken** instances were used as **latency to arising** if the difference was less than 120 minutes. Otherwise, it was marked as N/A.

5. Extract sleep architecture features.	(A) Extract durations of sleep stages between **sleep onset time** and **sleep offset time** from Fitbit sleep stages data. These are marked as **light sleep duration**, **deep sleep duration**, and **REM sleep duration**. (B) **Total sleep time (TST)** was obtained by adding light, deep and REM sleep durations. The ratios of duration of each sleep stage and TST were calculated to derive proportion of light, REM and deep sleep.
6. Extract sleep continuity features	Calculate the number of "awake" stage instances from Fitbit sleep stages data between **sleep onset time** and **sleep offset time**. That number is taken as **Number of Awakenings**.
	The sum of the duration of the awakenings is taken as **Wake After Sleep Onset**.
	Derive **Sleep Efficiency** as (light sleep duration + deep sleep duration + rem sleep duration) / (light sleep duration + deep sleep duration + rem sleep duration + SPP + Latency to Arising + Wake After Sleep Onset)
7. Assign **Single-item Sleep Quality Scale (SSQS)** to the extracted features.	For extracted sleep features, the corresponding **SSQS rating** was assigned based on the participant's first self-report provided after awakening from that sleep period. SSQS ratings were included only when the calendar date of the SSQS matched the wake-up date of the extracted sleep episode. Participants were not permitted to rate the previous night's sleep after 23:59 on the wake-up day.

Table S4. LME model results to describe the relationship between passively derived sleep features and SSQS ratings for autistic and non-autistic participants

	Autistic	**Non-autistic**
Feature	**LME Coefficient (p); 95% CI**	**LME Coefficient (p); 95% CI**
Sleep Onset Time	-0.026 (0.601); -0.125, 0.072	-0.25 (<0.001); -0.337, -0.164

Sleep Offset Time	0.174 (<0.001); 0.077, 0.272	0.141 (0.001); 0.061, 0.222
Sleep Preparation Period	-0.038 (0.476); -0.141, 0.066	-0.061 (0.079); -0.129, 0.007
Number of Awakenings	-0.034 (0.489); -0.131, 0.062	0.012 (0.725); -0.053, 0.077
Wake After Sleep Onset	-0.052 (0.29); -0.149, 0.044	-0.025 (0.431); -0.089, 0.038
Latency to Arising	0.055 (0.242); -0.037, 0.147	0.014 (0.651); -0.046, 0.073
Total Sleep Time	0.25 (<0.001); 0.16, 0.341	0.313 (<0.001); 0.248, 0.378
Sleep Efficiency	0.179 (<0.001); 0.087, 0.271	0.189 (<0.001); 0.124, 0.254
Proportion of Light Sleep	-0.096 (0.042); -0.189, -0.003	-0.06 (0.098); -0.131, 0.011
Proportion of REM Sleep	0.153 (0.001); 0.059, 0.247	0.144 (<0.001); 0.072, 0.215
Proportion of Deep Sleep	-0.022 (0.65); -0.117, 0.073	-0.064 (0.069); -0.134, 0.005

Table S5. Data availability for excluded participants

Group	**ID**	**Days SSQS available**	**Days primary sleep available**	**Percent Fitbit wear time at night (9pm-9am)**	**pRMT available**
Non-autistic	CONTROL_P18	0	28	85.7	27
Non-autistic	CONTROL_P26	0	0	0	0
Non-autistic	CONTROL_P32	0	25	82.0	23
Non-autistic	CONTROL_P36	28	0	0	24
Non-autistic	S2_P13	0	2	9.2	2
Autistic	S1_P31	0	0	0	4
Autistic	S1_P34	6	0	14.9	10
Autistic	S1_P35	24	0	20.6	27
Autistic	S1_P45	16	0	0	1
Autistic	S2_P12	26	0	0	28
Autistic	S2_P19	26	0	17.8	28
Autistic	S2_P24	26	0	19.5	11

Autistic	S2_P38	26	0	0	13
Autistic	S2_P48	2	1	5.0	2
Autistic	S2_P51	23	0	4.5	0

Table S6. Agglomerative clustering results.

Linkage	Number of clusters	Silhouette Score
Ward	2	0.248
Ward	3	0.228
Ward	4	0.222
Ward	5	0.224
Complete	2	0.270
Complete	**3**	**0.272**
Complete	4	0.234
Complete	5	0.184

Table S7. Individual Cluster participants and days summary

Cluster	Group	Number of Participant-Days	Percent of Participant-Days
a	autistic	191	42.73
a	nonautistic	235	36.43
b	autistic	215	48.10
b	nonautistic	297	46.05
c	autistic	41	9.17
c	nonautistic	113	17.52

Figures

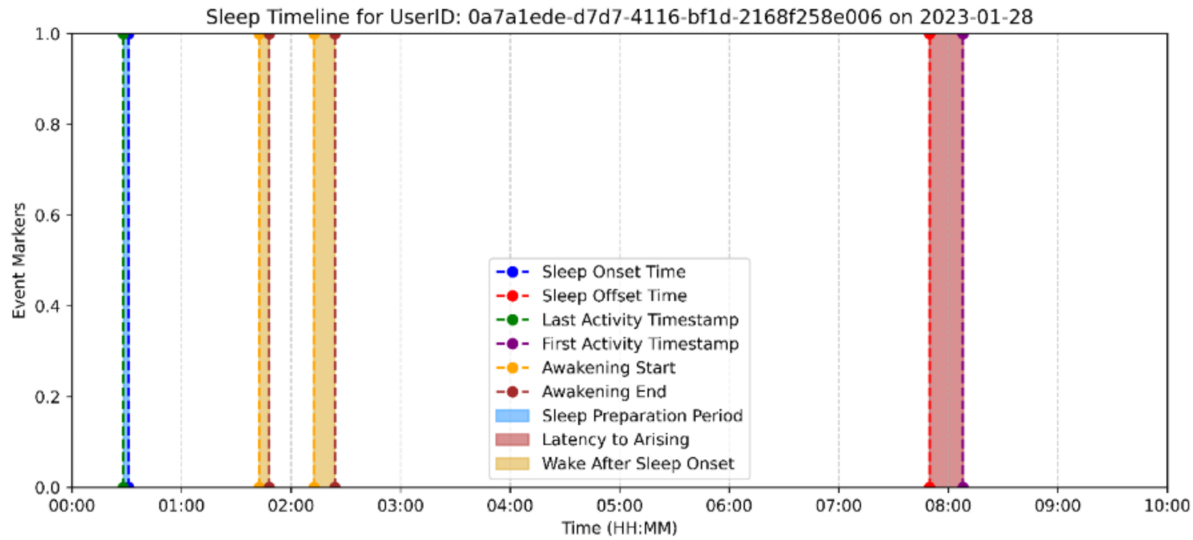

Figure S1. A sleep timeline diagram depicting different components for sleep for one participant

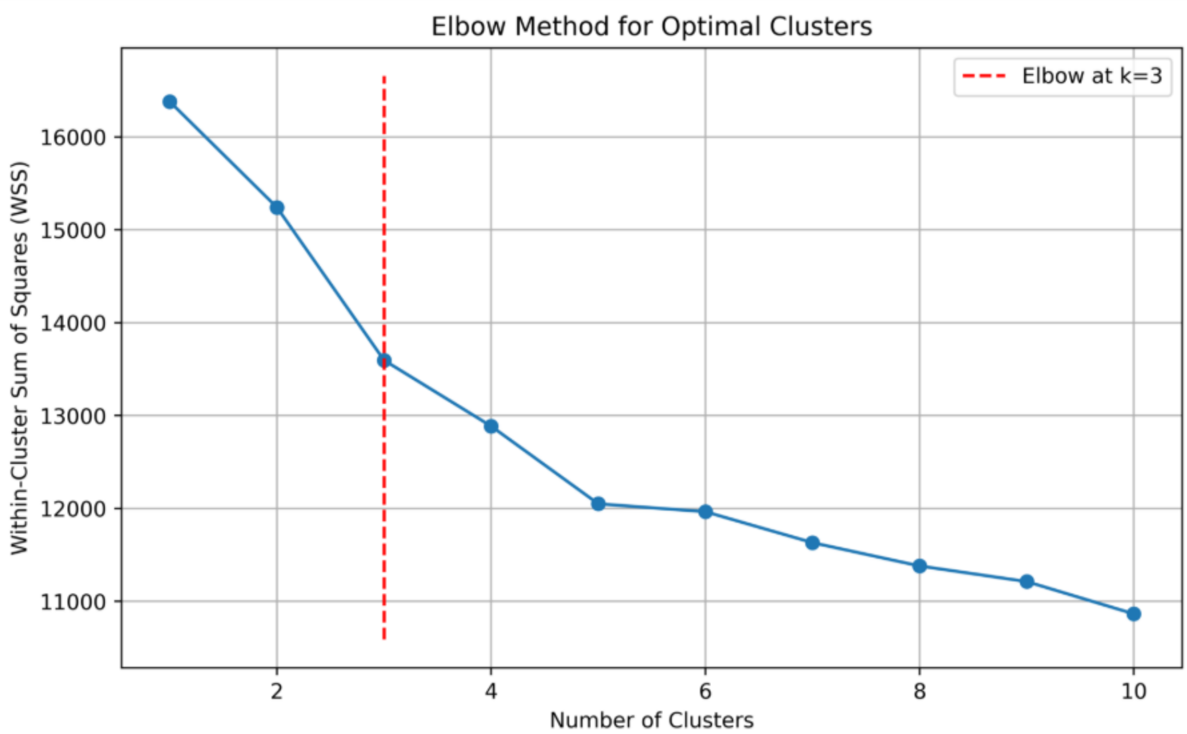

Figure S2. Elbow method for generating optimal number of clusters.