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Sleep Diagnostics

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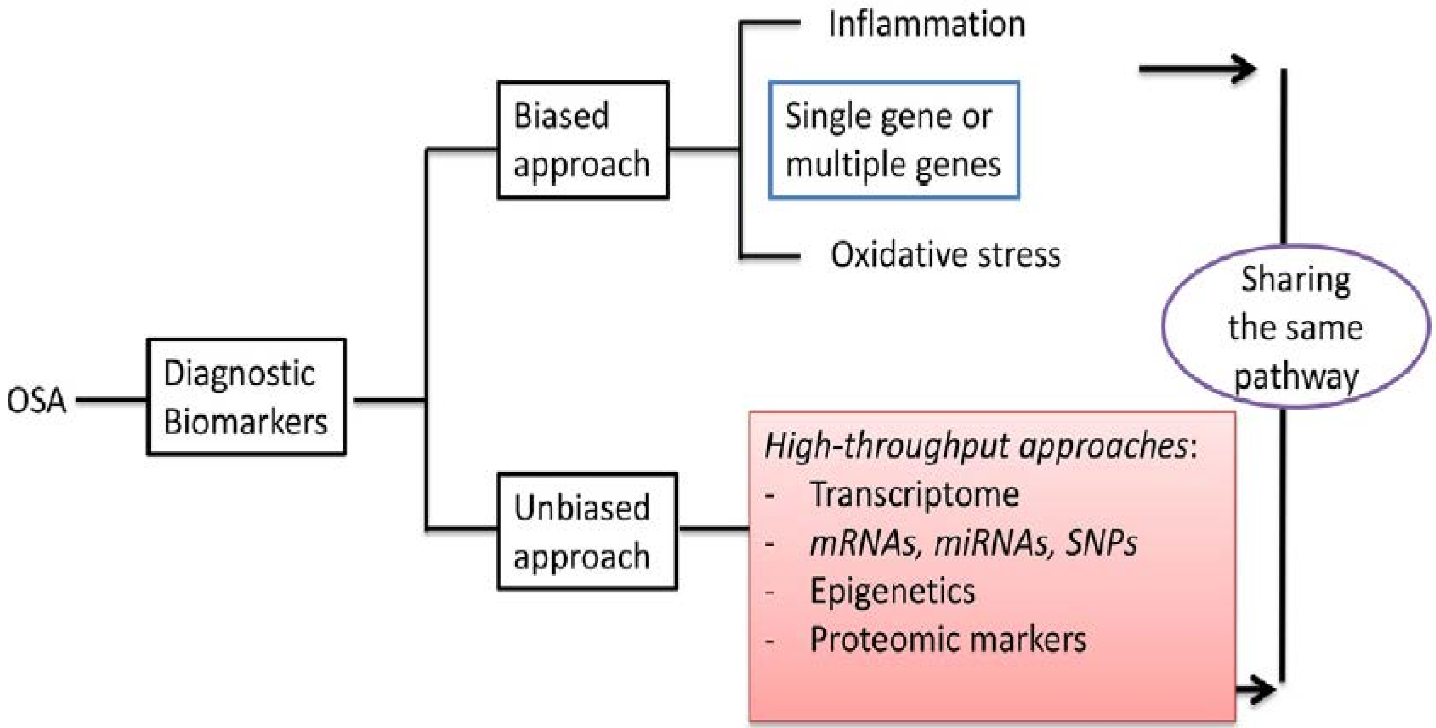
Conflicts of Interest

- Royalties from UPTODATE as an author and editor
- Received grant monies and was on advisory council for Jazz Pharmaceuticals (2017-2018)

- Biomarkers
- Consumer Devices
  - Assessing sleep
  - Sleep disorders
- PSG intensity

Ideal Biomarker

- disease specificity
- mandatory presence in all affected patients
  - high sensitivity and specificity
- reversibility following proper treatment
- detectability before patients develop clinical manifestations
- reflect severity of the disease and provide indicative information over the cumulative history of the disease,
- enable a cut-off value with minimal overlap between normal and disease
- Minimize the total cost and burden of diagnosing a patient



Sleep Med Clin 11 (2016) 213–226

Potential biomarkers identified (n = 31)

Potential Biomarkers	Children	Adults
8-isoprostane	✓	
Adiponectin	✓	
AGEs		✓
AOPP		✓
APOEe4	✓	
Calprotectin		✓
Catecholamines	✓	
Catestatin	✓	
CRP	✓	✓
Cystatin C		✓
FFA		✓
FRAP		✓
FRAS		✓
Fructosamine		✓
GGT		✓
IL-6	✓	✓
IL-8		✓
HOMA	✓	
KL-6		✓
Leptin		✓
Lipid profiles		✓
MRP8/14	✓	
NP		✓
Resistin		✓
sTNF-RI		✓
S100B		✓
sVCAM-1		✓
TAC		✓
TBARS		✓
TNF-α	✓	
Urinary Neurotransmitters	✓	

OSA

- Types:
  - Blood
  - Urine
  - Exhaled breath condensate
  - Saliva
- Diagnostic and Prognostic

Sleep Medicine 16 (2015) 347–357

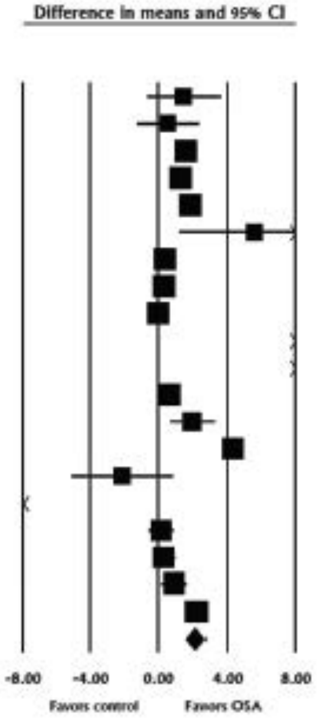
Interleukin - 6

- 18 studies
- Studied in both adults and children
- Cytokine in macrophages and lymphocytes
- May be more associated with obesity as some studies that showed higher levels were less positive or even not significant after correction for BMI
- Levels do change with CPAP in some but not all studies

Pulmonary Medicine
Volume 2014, Article ID 930535, 15 pages
http://dx.doi.org/10.1155/2014/930535

Figure 5—IL-6, one group standardized mean difference, OSA versus controls

Study name	Difference in means	Lower limit	Upper limit	p-Value
Alberti et al 2003	1.500	-0.603	3.603	0.162
Arias et al 2008	0.600	-1.244	2.444	0.524
Bravo et al 2007 A	1.680	1.567	1.793	0.000
Bravo et al 2007 B	1.360	1.193	1.527	0.000
Bravo et al 2007 C	1.940	1.787	2.093	0.000
Ciftci et al 2004	5.590	1.273	9.907	0.011
Constantinidis et al 2008 A	0.420	0.357	0.483	0.000
Constantinidis et al 2008 B	0.400	0.336	0.464	0.000
Fornadi et al 2012	0.020	-0.144	0.184	0.811
Harsch et al 2007	3700.000	3306.116	4093.884	0.000
Liu et al 2000	37.980	35.401	40.559	0.000
Liu et al 2011 A	0.700	0.460	0.940	0.000
Liu et al 2011 B	2.010	0.775	3.245	0.001
Roytblat et al 2000 A	4.300	3.755	4.845	0.000
Roytblat et al 2000 B	-2.110	-5.092	0.872	0.165
Roytblat et al 2000 C	-37.550	-51.268	-23.832	0.000
sahlman et al 2010	0.220	-0.509	0.949	0.554
Steiropolus et al 2010	0.370	-0.276	1.016	0.262
Thomopoulos et al 2009	0.976	0.246	1.706	0.009
Vgontzas et al 1997	2.230	1.701	2.759	0.000
	2.160	1.623	2.697	0.000



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Citation: Nadeem R; Molnar J; Madbouly EM; Nida M; Aggarwal S; Sajid H; Naseem J; Loomba R. Serum inflammatory markers in obstructive sleep apnea: a meta-analysis. *J Clin Sleep Med* 2013;9(10):1003-1012.

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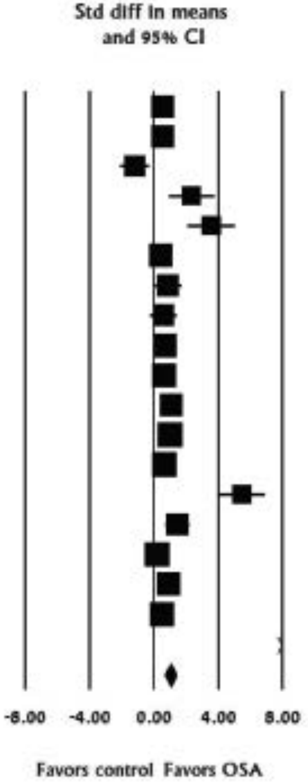
TNF - alpha

- Pro-inflammatory cytokine released during acute inflammation
- Participates in cell signaling leading to necrosis or apoptosis
- Associated with excessive daytime sleepiness, nocturnal sleep disturbance, hypoxia
- Higher levels noted in morning and after SDB events in OSA patients
- Conflicting studies on whether it is reduced after CPAP
- Interaction may also be related to degree of obesity

Pulmonary Medicine
Volume 2014, Article ID 930535, 15 pages
http://dx.doi.org/10.1155/2014/930535

Figure 3—TNF-α, one group standardized mean difference, OSA versus controls

Study name	Std diff in means	Lower limit	Upper limit	p-Value
	Statistics for each study			
Alberti et al 2003	0.545	-0.103	1.194	0.099
Arias et al 2008	0.545	-0.085	1.175	0.090
Bravo et al 2007 A	-1.185	-2.072	-0.298	0.009
Bravo et al 2007 B	2.349	0.955	3.743	0.001
Bravo et al 2007 C	3.573	2.103	5.042	0.000
Ciftci et al 2004	0.433	-0.087	0.952	0.102
Constantinidis et al 2008 A	0.886	0.072	1.701	0.033
Constantinidis et al 2008 B	0.588	-0.213	1.389	0.150
Fornadi et al 2012	0.697	0.234	1.160	0.003
Kanbay et al 2008	0.630	0.228	1.032	0.002
Kobayashi et al 2006	1.079	0.452	1.707	0.001
Li et al 2010 A	1.002	0.714	1.289	0.000
Li et al 2010 B	0.663	0.371	0.955	0.000
Liu et al 2000	5.478	4.088	6.868	0.000
Ryan et al 2005	1.474	0.736	2.211	0.000
Sahlman et al 2010	0.218	-0.160	0.595	0.258
Steiropolus et al 2010	0.905	0.363	1.447	0.001
Thomopoulos et al 2009	0.495	0.148	0.842	0.005
Vgontzas et al 1997	11.409	7.935	14.883	0.000
	1.024	0.674	1.394	0.000



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CRP

- Inflammatory marker, active role in atherogenesis
- Studies in both adults and children
- Mainly produced in the liver
- Multiple studies with varied results
- As with others, relationship is altered by obesity
- High CRP may indicate risk for developing CV events in OSA patients – further study needed
- Study in children suggested high levels of HS-CRP may ID children at high risk for cognitive morbidity

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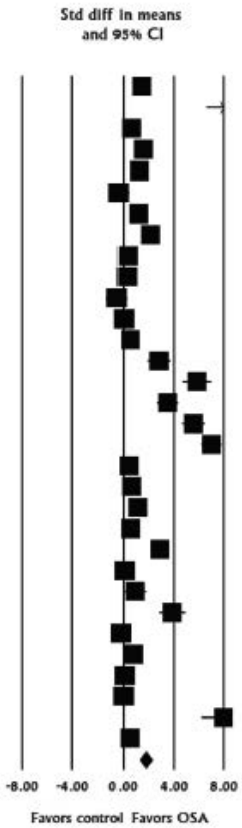
Figure 1—CRP, one group standardized mean difference, OSA versus controls

Study name	Std diff in means	Lower limit	Upper limit	p-Value
Barcelo et al 2004 A	1.426	0.743	2.109	0.000
Barcelo et al 2004 B	8.586	6.628	10.544	0.000
Barcelo et al 2011	0.625	0.365	0.885	0.000
Bhushan et al 2008 A	1.546	1.034	2.057	0.000
Bhushan et al 2008 B	1.243	0.827	1.659	0.000
Carneiro et al 2009	-0.321	-1.057	0.416	0.394
Chein et al 2011	1.213	0.662	1.763	0.000
Drager et al 2010	2.122	1.718	2.525	0.000
Dziewas et al 2007	0.394	0.026	0.761	0.036
Fornadi et al 2012	0.335	-0.120	0.790	0.149
Guasti et al 2009	-0.502	-1.281	0.277	0.207
Guilleminault et al 2004	0.092	-0.220	0.404	0.564
Guven et al 2012	0.528	0.058	0.999	0.028
Harsch et al 2007	2.826	1.939	3.714	0.000
Hayashi et al 2006 A	5.835	4.711	6.959	0.000
Hayashi et al 2006 B	3.504	2.670	4.339	0.000
Hayashi et al 2006 C	5.582	4.656	6.508	0.000
Iesato et al 2007	6.991	6.212	7.771	0.000
Kapsimalis et al 2008 A	0.409	-0.232	1.051	0.211
Kapsimalis et al 2008 B	0.646	-0.004	1.297	0.052
Liu et al 2011 A	1.136	0.468	1.804	0.001
Liu et al 2011 B	0.530	0.015	1.045	0.044
Meng et al 2009	2.881	2.370	3.392	0.000
Sahlman et al 2010	0.146	-0.231	0.523	0.447
Sariman et al 2011	0.930	0.100	1.759	0.028
shamsuzzaman et al 2002	3.881	2.853	4.908	0.000
Sharma et al 2008 A	-0.143	-0.611	0.324	0.547
Sharma et al 2008 B	0.822	0.253	1.392	0.005
Steiropolus et al 2010	0.166	-0.352	0.685	0.530
Thomopoulos et al 2009	0.057	-0.285	0.399	0.744
Yokoe et al 2003	7.988	6.203	9.774	0.000
Yumino et al 2007	0.514	0.088	0.941	0.018
	1.774	1.284	2.263	0.000

Statistics for each study



Citation: Nadeem R; Molnar J; Madbouly EM; Nida M; Aggarwal S; Sajid H; Naseem J; Loomba R. Serum inflammatory markers in obstructive sleep apnea: a meta-analysis. *J Clin Sleep Med* 2013;9(10):1003-1012.

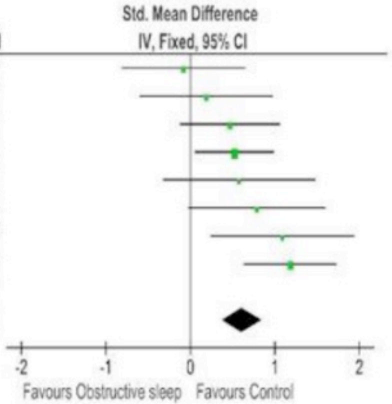
CRP/OSA Meta-analysis

- 219 OSA vs 116 controls
  - Adult non-smoking matched for BMI, age, gender
- 5 studies with low heterogeneity

	Obstructive sleep apnea			Control				Std. Mean Difference
Study or Subgroup	Mean	SD	Total	Mean	SD	Total	Weight	IV, Fixed, 95% CI
Carneiro et al 2009	0.83	0.56	16	0.91	1.23	13	10.2%	-0.08 [-0.82, 0.65]
Minoguchi et al 2006 (mild)	0.09	0.09	20	0.07	0.13	9	8.8%	0.19 [-0.60, 0.98]
Ciccone et al 2014 (mild)	0.132	0.048	26	0.108	0.053	20	15.7%	0.47 [-0.12, 1.06]
Guven et al 2012	0.403	0.358	47	0.241	0.195	29	24.7%	0.52 [0.05, 0.99]
Minoguchi et al 2005 (mild)	0.15	0.11	13	0.09	0.08	8	6.7%	0.58 [-0.33, 1.48]
Minoguchi et al 2006 (moderate severe)	0.23	0.22	20	0.07	0.13	9	8.2%	0.79 [-0.03, 1.60]
Minoguchi et al 2005 (moderate-severe)	0.28	0.19	23	0.09	0.08	8	7.5%	1.09 [0.23, 1.94]
Ciccone et al 2014 (moderate-severe)	0.184	0.067	54	0.108	0.053	20	18.2%	1.18 [0.63, 1.73]
Total (95% CI)			219			116	100.0%	0.61 [0.38, 0.84]

Heterogeneity: $Chi^2 = 10.46$, $df = 7$ ($P = 0.16$); $I^2 = 33\%$

Test for overall effect: $Z = 5.11$ ($P < 0.00001$)



https://doi.org/10.1080/1354750X.2019.1600025

Quantitative EEG in OSA

- Examine power spectral analysis by transforming amplitude vs time to amplitude vs frequency; essentially quantifies the amplitude and prevalence of different frequency sine waves
  - Slowing of the EEG associated with sleepiness and fatigue in wake and changes in sleep EEG may be associated with learning and memory
- 24 studies examined qEEG in OSA

Sleep Medicine Reviews 36 (2017) 29–42

Quantitative EEG in OSA

- Waking EEG and severity of OSA: heterogeneous results
- Waking EEG and daytime sleepiness: seems to correlate better with subjective sleep measure than with objective sleep measures
- Waking EEG and performance tasks (PVT, driving simulator) show some correlation but often need more sophisticated signal processing technique
- Waking EEG after CPAP – reduction of theta power; variable effects noted on delta power

Sleep Medicine Reviews 36 (2017) 29–42

Quantitative EEG in OSA

- Effect on sleep EEG:
  - reduced slow wave activity with the exception of OHS who may have higher SWA
  - Reduced spindle activity
  - Effect of CPAP may reverse SWA reduction
- Conclusion that more sophisticated and standardized analysis is needed with better controls

Sleep Medicine Reviews 36 (2017) 29–42

REM Sleep Behavior Disorder: Potential biomarkers

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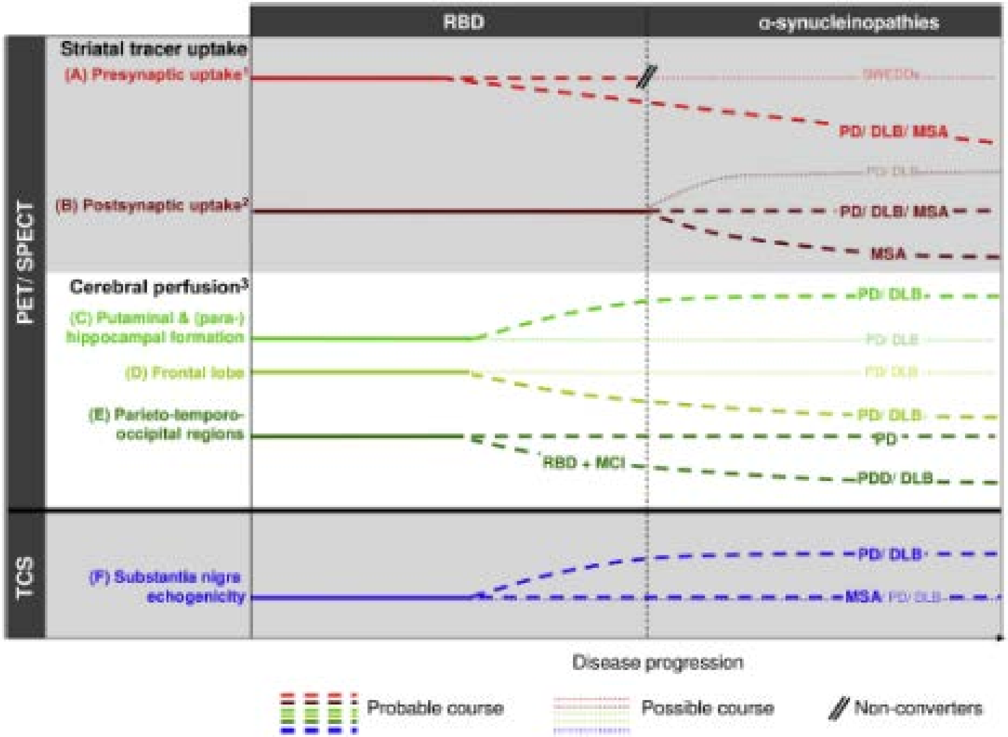
- Might allow early prognostication
- DAT scan (radiotracer that measures presynaptic dopamine transporter density)
- ^{18}F-FDG Pet scan (metabolic increases in pons, thalamus, medial frontal and sensorimotor areas, hippocampus, temporal gyri, posterior cerebellum)
- Transcranial sonography (echogenicity of brain tissue) – see striatal nigra hyperechogenecity
- None of these are quite ready for prime time

Sleep Medicine Reviews 34 (2017) 23–33

REM Sleep Behavior Disorder: Potential biomarkers



Sleep Medicine Reviews 34 (2017) 23–33

Consumer Devices for Sleep and Sleep Disorders

How many times have you heard…

- “my Fitbit says I am having lots of disruptions in my sleep”
- “my sleep tracker says I am not getting enough deep sleep; or dream sleep…”
- “should I go buy a fitness device that monitors my sleep? which one is best?”

Consumer Devices

- Search for sleep terms on smartphones, get about 2500 apps
- Modalities:
  - Mobile device (smartphones and tablets)
  - Wearable technology
  - Unique physical devices embedded into sleep environment
  - Online programs (desktop or website platforms)
  - Accessory devices that may interact with mobile devices

Consumer Sleep Technologies: A Review of the Landscape

Ping-Ru T. Ko, MD[1]; Julie A. Kientz, PhD[2]; Eun Kyoung Choe, PhD[3]; Matthew Kay, MS[4]; Carol A. Landis, PhD, RN, FAAN[5]; Nathaniel F. Watson, MD, MSc[6]

- Very nice review of available types and brands of devices
- Note lack of validation for many
- Do raise consumer awareness of sleep
- Many pros and cons!

J Clin Sleep Med 2015;11(12):1455–1461.

Mobile devices

- 77% of adults own a smartphone!!
- Sleep tracking, alarms, sleep and dream logging
- May facilitate sleep with graphics, music or sounds, professional hypnotists
- Often sit on mattress and may be affected by other body sleep (bedpartner, animal) or type of mattress (waterbed, pillowtop)
- “Smart alarm” – awaken you from light sleep; require you to do a task so you can’t go back to sleep integrate with a lamp that slowly illuminates
- Detect snoring, sleep talking
- Awaken when snoring (vibrates or makes a noise)

J Clin Sleep Med 2015;11(12):1455–1461.

EMERGING TECHNOLOGIES

Rate My Sleep: Examining the Information, Function, and Basis in Empirical Evidence Within Sleep Applications for Mobile Devices

Peta A. Lee-Tobin, MProfPsych[1,2]; Rowan P. Ogeil, PhD[1,2]; Michael Savic, PhD[1,2]; Dan I. Lubman, PhD, FRANZCP, FAChAM[1,2]
[1]Eastern Health Clinical School, Monash University, Box Hill, Victoria, Australia; [2]Turning Point, Eastern Health, Fitzroy, Victoria, Australia

- Apps in Google Play store
- Primary sleep complaint addressed:
  - OSA (n = 23, 30.3%)
  - insomnia (n = 9, 11.8%)
  - Sleep cycles or circadian rhythms (n = 32, 42.1%)
  - general sleep (n = 8, 10.5%)
- Categorized as either “health & fitness” (n = 46, 60.5%) or “medical” (n = 20, 26.3%) apps
- Most were free to download (n = 61, 80.3%); maximum cost of $6.82

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[1]Eastern Health Clinical School, Monash University, Box Hill, Victoria, Australia; [2]Turning Point, Eastern Health, Fitzroy, Victoria, Australia

- 10 most downloaded sleep apps
  - rating of 4 or more stars (representing high user satisfaction)
  - only one of these apps was identified as containing evidence
- 10 least downloaded apps
  - 8 /10 were given ratings under 4 stars
  - most of them focusing on OSA

J Clin Sleep Med. 2017;13(11):1349–1354.

Smartphone Applications to Support Sleep Self-Management: Review and Evaluation

Yong K. Choi, MPH[1]; George Demiris, PhD[2]; Shih-Yin Lin, PhD, MPH, MM[1]; Sarah J. Iribarren, PhD, RN[1]; Carol A. Landis, PhD, RN[1];
Hilaire J. Thompson, PhD, RN, ARNP, CNRN, AGACNP-BC[1]; Susan M. McCurry, PhD[1]; Margaret M. Heitkemper, PhD, RN[1]; Teresa M. Ward, PhD, RN[1]

Table 1—MARS items and subscales criteria.

App Quality Scoring Criteria	Subscales
1. Engagement	1.1 Entertainment 1.2 Interest 1.3 Customization 1.4 Interactivity 1.5 Target group
2. Functionality	2.1 Performance 2.2 Ease of use 2.3 Navigation 2.4 Gestural design
3. Aesthetics	3.1 Layout 3.2 Graphics 3.3 Visual appeal: how good does the app look?
4. Information	4.1 Accuracy of app description 4.2 Goals 4.3 Quality of information 4.4 Quantity of information 4.5 Visual information 4.6 Credibility 4.7 Evidence base
5. Subjective quality	5.1 Would you recommend this app? 5.2 How many times do you think you would use this app? 5.3 Would you pay for this app? 5.4 What is your overall star rating of the app?

J Clin Sleep Med. 2018;14(10):1783–1790.

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Table 4—Description of top 5 apps combining MARS and IMS functionality scores.

Name	Platform	Cost, US $	# of Installs*	Star Rating	MARS Score	IMS Score	Tracking Type
Sleep as Android Unlock	Google/Amazon	3.99	500,000–1,000,000	5	4.0	11	Both
Sleep Center Free	Apple	Free	N/R	NA	4.0	10	Both
Good Morning Alarm Clock	Apple/Google	Free	1,000,000–5,000,000	4	3.7	11	Automatic
Samsung Health	Google	Free	100,000,000–500,000,000	4	3.7	11	Manual
Snail Sleep	Google/Amazon	Free	100,000–500,000	4	3.5	10	Automatic

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- “However, it is critically important to highlight that such sleep parameters calculated by the custom algorithms of the sleep self-management apps have yet to be successfully validated against results obtained by polysomnography (PSG), the gold standard
- …only three apps (Sleep Time,15 MotionX 24/7,16 Sleep Cycle17) have been formally evaluated for clinical validity comparing the parameters reported by the apps and those obtained by PSG.
- The validation studies have shown that the sleep parameters by the apps poorly correlated with PSG and failed to accurately reflect the sleep stages and thus deemed not useful as a clinical tool.”

J Clin Sleep Med. 2018;14(10):1783–1790.

http://dx.doi.org/10.5664/jcsm.4840

Is There a Clinical Role For Smartphone Sleep Apps? Comparison of Sleep Cycle Detection by a Smartphone Application to Polysomnography

Sushanth Bhat, MD[1]; Ambra Ferraris, MD[1]; Divya Gupta, MD[1]; Mona Mozafarian, MD[1]; Vincent A. DeBari, PhD[2]; Neola Gushway-Henry, MD[1]; Satish P. Gowda, MD[1]; Peter G. Polos, MD, PhD[1]; Mitchell Rubinstein, RPSGT[1]; Huzaifa Seidu, MD[1]; Sudhansu Chokroverty, MD[1]

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- 20 subjects – no history of sleep disorders
- Download app (Azumio) then used at home for 5 nights (so app can become acclimated)
- Underwent PSG study and questionnaire

Figure 1

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Table 3—Comparison of absolute parameters obtained by polysomnography and provided by the app for subjects in the study (n = 20).

	PSG	App
Sleep efficiency (%)	86.6 ± 8.0	86.5 ± 6.3
Light sleep (%)	60.7 ± 12.4	32.8 ± 13.7[a]
Deep sleep (%)	39.6 ± 11.9	50.6 ± 8.9[b]
Traditional sleep latency (min)	11.6 ± 14.5	27.3 ± 16.2[a]
Sustained sleep latency (min)	17.3 ± 18.4	27.3 ± 16.2[c]

Table 7—App performance in awakening patients out of light sleep during the in-laboratory polysomnography.

	Number of Subjects
Awake at the time of app alarm	3/20 (15%)
Asleep and in light sleep at the time of app alarm	14/17 (82.4%)
Asleep and in deep sleep at the time of app alarm	3/17 (17.6%)

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Table 4—Sleep-wake detection by the app based on epoch-by-epoch comparison.

Total number of PSG sleep epochs	Total number of epochs correctly scored by the app as sleep (regardless of stage)	Sensitivity	Specificity	PPV	NPV
473	425	89.9% (CI 86.8–92.4)	50.0% (CI 36.1–63.9%)	94.0% (CI 91.4–96.0)	36.0% (CI 25.2–47.9)

CI, confidence interval; NPV, negative predicted value; PPV, positive predicted value; PSG, polysomnography.

Table 5—Statistical performance of intrasleep staging by the app based on epoch-by-epoch comparison.

Sleep stage	Total number of PSG epochs	Total number of epochs correctly staged by the app	Sensitivity	Specificity	PPV	NPV
Light sleep	283	96	33.9% (CI 28.4–39.8)	67.6% (CI 61.4–73.5)	54.9% (CI 47.2–62.4)	46.9% (CI 41.6–52.2)
Deep sleep	190	119	62.6% (CI 55.3–69.5)	53.1% (CI 47.6–58.5)	43.0% (CI 37.1–49.0)	71.6% (CI 65.6–77.1)

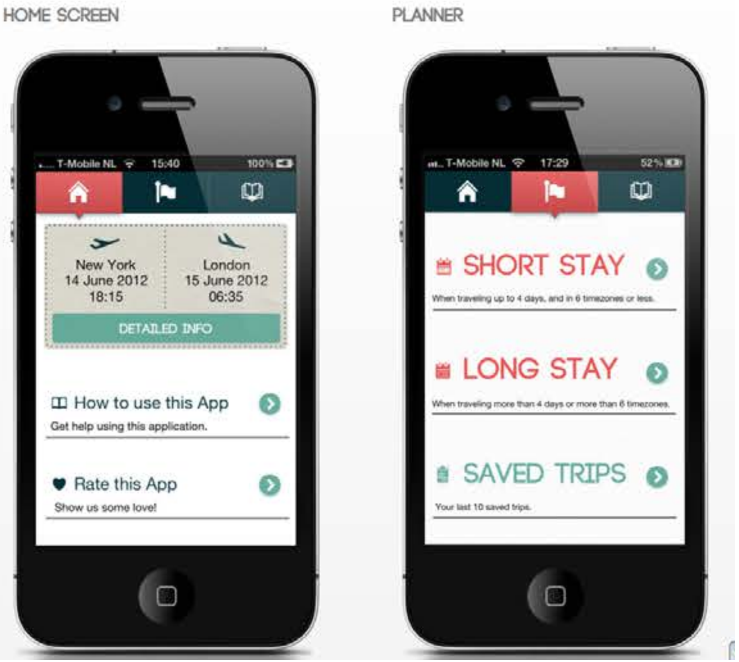
CI, confidence interval; NPV, negative predicted value; PPV, positive predicted value; PSG, polysomnography.

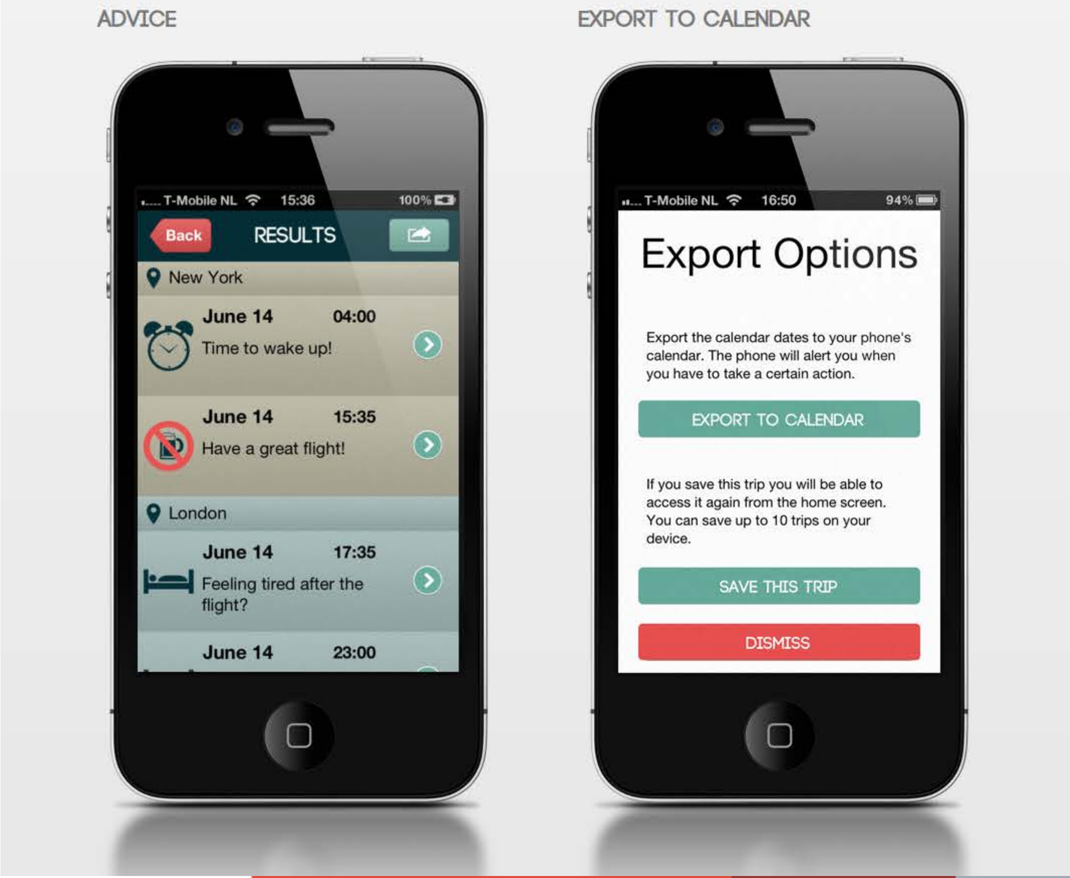
Table 6—Stage-wise accuracy of app staging based on epoch-by-epoch comparison.

	All epochs sleep-wake detection only	All epochs staging	Wake	N1	N2	N3	REM
Number of epochs	527	527	54	11	272	111	79
Accuracy	85.9%	45.9%	50.0%	54.5%	33.0%	71.2%	50.6%

N1, stage 1 sleep; N2, stage 2 sleep; N3, stage 3 sleep; REM, rapid eye movement sleep.

Apps for Jet Lag




ADVICE
EXPORT TO CALENDAR
T-Mobile NL 15:36 100%
Back
RESULTS
New York
June 14 04:00
Time to wake up!
June 14 15:35
Have a great flight!
London
June 14 17:35
Feeling tired after the flight?
June 14 23:00
T-Mobile NL 16:50 94%
Export Options
Export the calendar dates to your phone's calendar. The phone will alert you when you have to take a certain action.
EXPORT TO CALENDAR
If you save this trip you will be able to access it again from the home screen. You can save up to 10 trips on your device.
SAVE THIS TRIP
DISMISS

Wearable devices

- Usually on wrist but can be in clothing or a pendant
- Track body movements, biometric info
- Often report “light”, “deep”, “REM” sleep
- Most not well validated or validation data not readily available

J Clin Sleep Med 2015;11(12):1455–1461.

Wearable devices

- Fitbit
- Jawbone
- Smartwatches
- Sleep Shepherd hat
- SleepImage

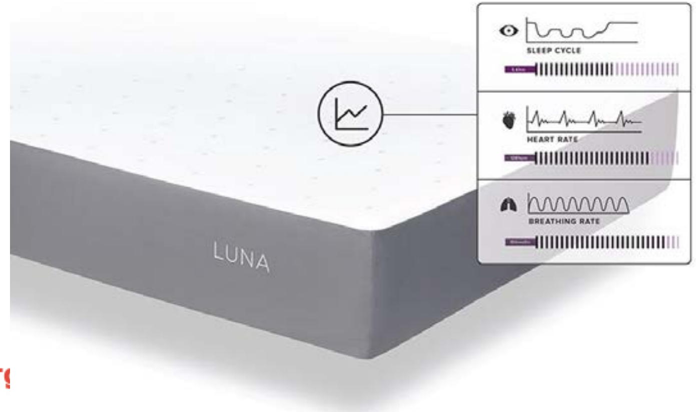
J Clin Sleep Med 2015;11(12):1455–1461.

Embedded platforms

- Physical devices embedded in sleep environment
- May use cameras, microphones
- Examples include:
  - Sleep number bed (remotely raises when snoring)
  - Tanita Sleep scan (Matt under mattress)
  - Luna (mattress cover) – can monitor sleep stage, has a smart alarm, change temperature

J Clin Sleep Med 2015;11(12):1455–1461.


Introducing the Sleep Number 360™ smart bed.
The only bed that goes to work when you go to sleep.
9:45PM
WARMS YOUR FEET TO SEND YOU TO SLEEP FASTER
10:00PM
ADJUSTS TO YOUR COMFORT ON BOTH SIDES–YOUR SLEEP NUMBER SETTING
1:00AM
SENSES YOUR HEART RATE, BREATHING AND MOVEMENT
1:01AM
EFFORTLESSLY RESPONDS TO YOU BY AUTOMATICALLY ADJUSTING TO YOUR NEEDS
3:45AM
SENSES SNORING AND GENTLY ELEVATES YOUR PARTNER'S HEAD
6:30AM
WAKES YOU FOR YOUR DAY AND SHOWS YOU HOW WELL YOU SLEPT


SLEEP CYCLE
HEART RATE
BREATHING RATE
LUNA

Validation of Contact-Free Sleep Monitoring Device with Comparison to Polysomnography

Asher Tal, MD[1]; Zvika Shinar, PhD[2]; David Shaki, MD[1]; Shlomi Codish, MD[3]; Aviv Goldbart, MD[1]

[1]Soroka Medical Center, Faculty of Health Sciences, Ben-Gurion University of the Negev; [2]EarlySense Ltd., Ramat Gan, Israel; [3]Clalit Health Services, Beer Sheva, Israel

- Tested this device during PSG in sleep lab (43) and then at home, one person in bed (7) and two persons in bed (13)
- Device set to distinguish REM, “light” sleep (N1+ N2), deep sleep (SWS)
- Detects RR, HR, movement

The ES sensor (left) is placed under the mattress under the estimated location of the patient’s chest. The ES device is considered a nonsignificant risk device because the sensor is placed under the mattress, does not come in contact with the subject, and does not require subject compliance.

JCSM 2017;13(3):517–522.

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A

Piezoelectric contact-free system	Reference Values (full PSG) Awake	REM	LS	SWS
Awake	9,482 (80.4%)	588 (5.4%)	3,710 (9.7%)	114 (1.1%)
REM	569 (4.8%)	5,844 (53.7%)	4,224 (11.1%)	308 (3.0%)
LS	1,477 (12.5%)	4,190 (38.5%)	24,771 (64.9%)	4,014 (39.7%)
SWS	265 (2.2%)	254 (2.3%)	5,471 (14.3%)	5,684 (56.2%)

B

Piezoelectric contact-free system	PSG Reference Wake	Asleep
Wake	9,482 (80.4%)	4,412 (7.5%)
Asleep	2,311 (19.6%)	54,760 (92.5%)

JCSM 2017;13(3):517–522.

EMERGING TECHNOLOGIES

Validation of Contact-Free Sleep Monitoring Device with Comparison to Polysomnography

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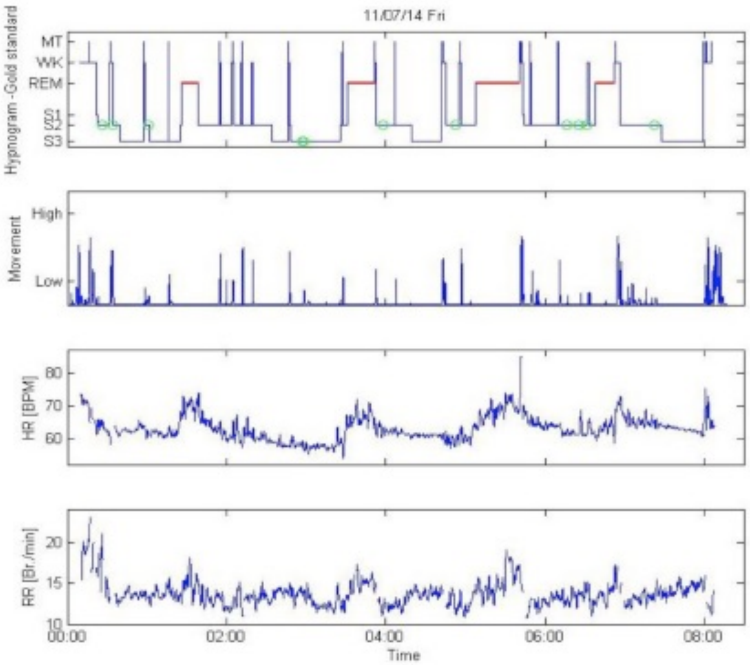

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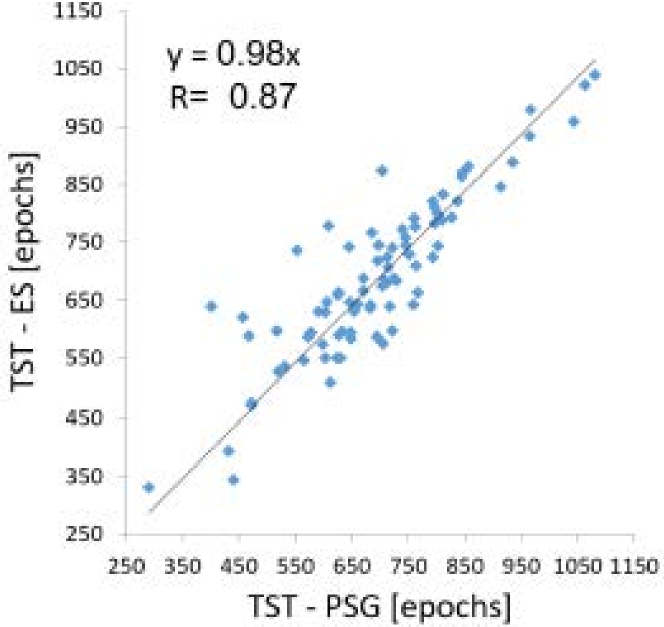
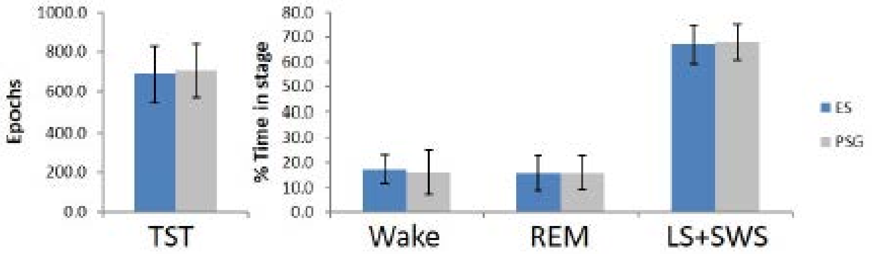


Figure 5—Comparison between data assessed by the EarlySense (ES) sensor (blue bars) and that derived from polysomnography (PSG) data (gray bars) for all nights (n = 85), including in the sleep laboratory and at home.



JCSM 2017;13(3):517–522.

Digital Health and Sleep-Disordered Breathing: A Systematic Review and Meta-Analysis

Talita Rosa, MD, MS[1]; Kersti Bellardi, MS[2]; Alonço Viana Jr, MD, MS[3]; Yifei Ma, MS[4]; Robson Capasso, MD[5]

Bed/Mattress-Based Sensors				
Studies: Cross-sectional studies with one-gate design (Agatsuma et al. 2009, Beattie et al. 2013, Takasaki et al. 2008, Tsukahara et al. 2014) and diagnostic case-control (Norman et al. 2014)				
AHI Threshold Subgroup	**Summary Accuracy (95% CI)**		**No. of Participants (Studies Included)**	**Studies Not Included**
	Sensitivity	**False Positive Rate**		
Overall	0.921 (0.870, 0.953)	0.203 (0.124, 0.314)	515 (5)	–
Cutoff 5 events/h	0.951 (0.789, 0.990)	0.395 (0.189, 0.647)	515 (5)	–
Cutoff 15 events/h	0.944 (0.886, 0.973)	0.155 (0.055, 0.366)	515 (5)	–
Cutoff 30 events/h	0.917 (0.833, 0.961)	0.113 (0.065, 0.191)	515 (5)	–

JCSM 2018; 14(9): 1605-1620

Digital Health and Sleep-Disordered Breathing: A Systematic Review and Meta-Analysis

Talita Rosa, MD, MS[1]; Kersti Bellardi, MS[2]; Alonço Viana Jr, MD, MS[3]; Yifei Ma, MS[4]; Robson Capasso, MD[5]

Contactless Devices (Other Than Bed/Mattress-Based Sensors)				
Studies: Cross-sectional studies with one-gate design (Abad et al. 2016, Davidovich et al. 2016, Espinoza-Cuadros et al. 2015, Nandakumar et al. 2015, Zaffaroni et al. 2013, Weinreich et al. 2014)				
AHI Threshold Subgroup	**Summary Accuracy (95% CI)**		**No. of Participants (Studies Included)**	**Studies Not Included**
	Sensitivity	**False Positive Rate**		
Overall	0.905 (0.839, 0.946)	0.217 (0.110, 0.383)	594 (6)	–
Cutoff 5 events/h	0.976 (0.899, 0.995)	0.487 (0.137, 0.851)	498 (5)	Davidovich et al. 2016
Cutoff 15 events/h	0.876 (0.760, 0.941)	0.136 (0.075, 0.235)	594 (6)	–
Cutoff 30 events/h	0.806 (0.695, 0.883)	0.066 (0.043, 0.101)	456 (4)	Davidovich et al. 2016, Weinreich et al. 2014

JCSM 2018; 14(9): 1605-1620

Digital Health and Sleep-Disordered Breathing: A Systematic Review and Meta-Analysis

Talita Rosa, MD, MS[1]; Kersti Bellardi, MS[2]; Alonço Viana Jr, MD, MS[3]; Yifei Ma, MS[4]; Robson Capasso, MD[5]

Contact Devices With Three or More Sensors

Studies: Cross-sectional studies with one-gate design (Benistant 2016), and diagnostic case-control with two-gate design (Al-Mardini et al. 2014)

AHI Threshold Subgroup	Summary Accuracy (95% CI)		No. of Participants (Studies Included)	Studies Not Included
	Sensitivity	False Positive Rate		
Overall	0.771 (0.466, 0.929)	0.094 (0.029, 0.269)	24 (2)	–
Cutoff 5 events/h	0.770 (0.171, 0.982)	0.134 (0.028, 0.459)	24 (2)	–

Contact Devices With Fewer Than Three Sensors

Studies: Cross-sectional studies with one-gate design (Dinç et al. 2014, Ozmen et al. 2011, Levendowski et al. 2015), and diagnostic case-control with two-gate design (Selvaraj et al. 2014)

AHI Threshold Subgroup	Summary Accuracy (95% CI)		No. of Participants (Studies Included)	Studies Not Included
	Sensitivity	False Positive Rate		
Overall	0.713 (0.594, 0.808)	0.099 (0.058, 0.166)	169 (4)	–
Cutoff 5 events/h	0.637 (0.392, 0.827)	0.077 (0.011, 0.392)	51 (2)	Ozmen et al. 2011, Selvaraj et al. 2014
Cutoff 15 events/h	0.716 (0.500, 0.865)	0.122 (0.049, 0.273)	169 (4)	–
Cutoff 30 events/h	0.450 (0.191, 0.740)	0.022 (0.001, 0.268)	31 (1)	Ozmen et al. 2011, Selvaraj et al. 2014, Levendowski et al. 2015

JCSM 2018; 14(9): 1605-1620

Talita Rosa, MD, MS[1]; Kersti Bellardi, MS[2]; Alonço Viana Jr, MD, MS[3]; Yifei Ma, MS[4]; Robson Capasso, MD[5]

- Devices that were bed/mattress-based were found to have the best sensitivity overall (0.921, 95% confidence interval [CI] 0.870, 0.953)
- The sensitivity of contactless devices to detect mild OSA cases was the highest of all groups (0.976, 95% CI 0.899, 0.995), but provided a high false positive rate (0.487, 95% CI 0.137, 0.851).
- The remaining groups of devices showed low sensitivity and heterogeneous results

JCSM 2018; 14(9): 1605-1620

Accessory Appliance Platforms

- Separate device that may or may not interact with mobile devices or internet
- Examples:
  - Specialized alarm clocks
  - Wakeup lights
  - EmWave – biofeedback device
  - Sense with Sleep pill – senses noise, light, temp, humidity, allergens then adjusts sound and light
  - Withings Aura – similar but adjust light spectrum

J Clin Sleep Med 2015;11(12):1455–1461.


SmartHomeDB.


emwave

What should you do when a patient wants to show you their phone app sleep data?

A. Tell them you don't believe the data so don't bother

B. Review the data and use it to guide your therapy decisions

C. Assess their dependence on the data and suggest discontinuation if it is causing anxiety

What should you do when a patient wants to show you their phone app sleep data?

A. Tell them you don't believe the data so don't bother
B. Review the data and use it to guide your therapy decisions
C. <u>Assess their dependence on the data and suggest discontinuation if it is causing anxiety</u>

Consumer Sleep Technology: An American Academy of Sleep Medicine Position Statement

Table 2—General principles of CST engagement.

- Clinicians should have a general awareness of CST and a readiness to discuss CST with patients.
- Clinicians should understand the general framework of devices and apps available and have a basic knowledge of available evidence or lack thereof.
- Most CSTs are not FDA cleared or validated clinical devices/ applications, but widespread accessibility and use by patients (and potential patients) may augment patient engagement.
- Data can be utilized as a tool for opening discussions with patients.
- Clinicians should recognize the patient's use of CST as a commitment to focus on sleep wellness.

J Clin Sleep Med 2018;14(5):877–880.

Table 4—Guidance for clinicians encountering data in a clinical setting.

- If/when data are presented by patients, it should be considered in the context of a comprehensive sleep evaluation and should not replace validated diagnostic instruments or treatments that have undergone rigorous scientific investigation.
- Discuss with the patient which biometric the CST is measuring (if known) and how this differs from gold-standard sleep measurement.
- Encourage the patient to evaluate their sleep based on subjective symptoms, clinical context, and validated diagnostic testing rather than CST data of unclear significance.
- Reconcile the patient's symptoms with the data presented by the CST, emphasizing that CST-derived information must be interpreted carefully in the context of clinical signs and symptoms.
- Present options for ongoing use of the CST (eg, to set personal goals, assess change over time).
- Patients utilizing CST may favor engaging with validated online therapies such as CBT-I
- If the patient has developed anxiety, unreasonable expectations, or inadequate sleep hygiene related to the use of the CST, consider encouraging the patient to discontinue use of the device either temporarily or permanently.

J Clin Sleep Med 2018;14(5):877–880.

Conclusion – Sleep Tracking Devices

- Consumer sleep tracking devices significantly over estimate total sleep time when compared to PSG (like actigraphy)
- In addition, data for specific parameters such as sleep onset latency, sleep efficiency, and sleep stage analysis are unreliable
- The basis for the sleep score/quality seems to be unclear
- How are they affected by bedpartners, pets, mattress, sleep disorders
- For the consumer – is “light sleep” good or bad? How much “deep sleep” is needed? Is REM sleep “light” or “deep”?

Co – morbidity in patients undergoing PSG over time

Analysis of the Complexity of Patient Undergoing Attended PSG in the Era of HSAT
Colaco B, et al. JCSM 2018; 14 (4): 631-640

- Mayo Clinic chart review
- Development of Polysomnogram Clinical Index (PSGCI)
- Premise: the complexity of patients undergoing PSG has increased since HSAT has become more popular
- This may have effects on staffing ratios, staff expertise, facility design and monitoring capabilities

Analysis of the Complexity of Patient Undergoing Attended PSG in the Era of HSAT
Colaco B, et al. JCSM 2018; 14 (4): 631-640

- 43,780 pts studied from 2005 – 2015
- Examined comorbidity indices (Charlson, Elixhauser)
  - Comorbidity = total burden of illness unrelated to the principal diagnosis
  - Both indices use ICD-9 or ICD-10 diagnosis codes
- Developed a pretest score that could be used to predict fall risk, staff ratio, etc
  - Included pt comorbid conditions + complexity of study being done

Sleep Study Complexity

Likert Scale Value	Type of study/PAP
1	Diagnostic Polysomnogram (PSG)
2	Polysomnogram with parasomnia protocol (requiring special precautions and monitoring)
3	PSG with oxygen therapy titration
4	PSG with CPAP and or BiPAP-S titration
5	PSG with CPAP and or BiPAP- S with oxygen therapy titration
6	PSG with advanced PAP therapy (ASV, Auto SV, BiPAP ST, IVAPS, AVAPS) titration
7	PSG with advanced PAP (other than CPAP or BiPAP-S) and oxygen therapy titration, Study with parasomnia protocol with PAP therapy with or without oxygen therapy titration
8	Portable PSG (hospital study)

Analysis of the Complexity of Patient Undergoing Attended PSG in the Era of HSAT
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- Mayo Clinic providers "rate" the patients from 0-3

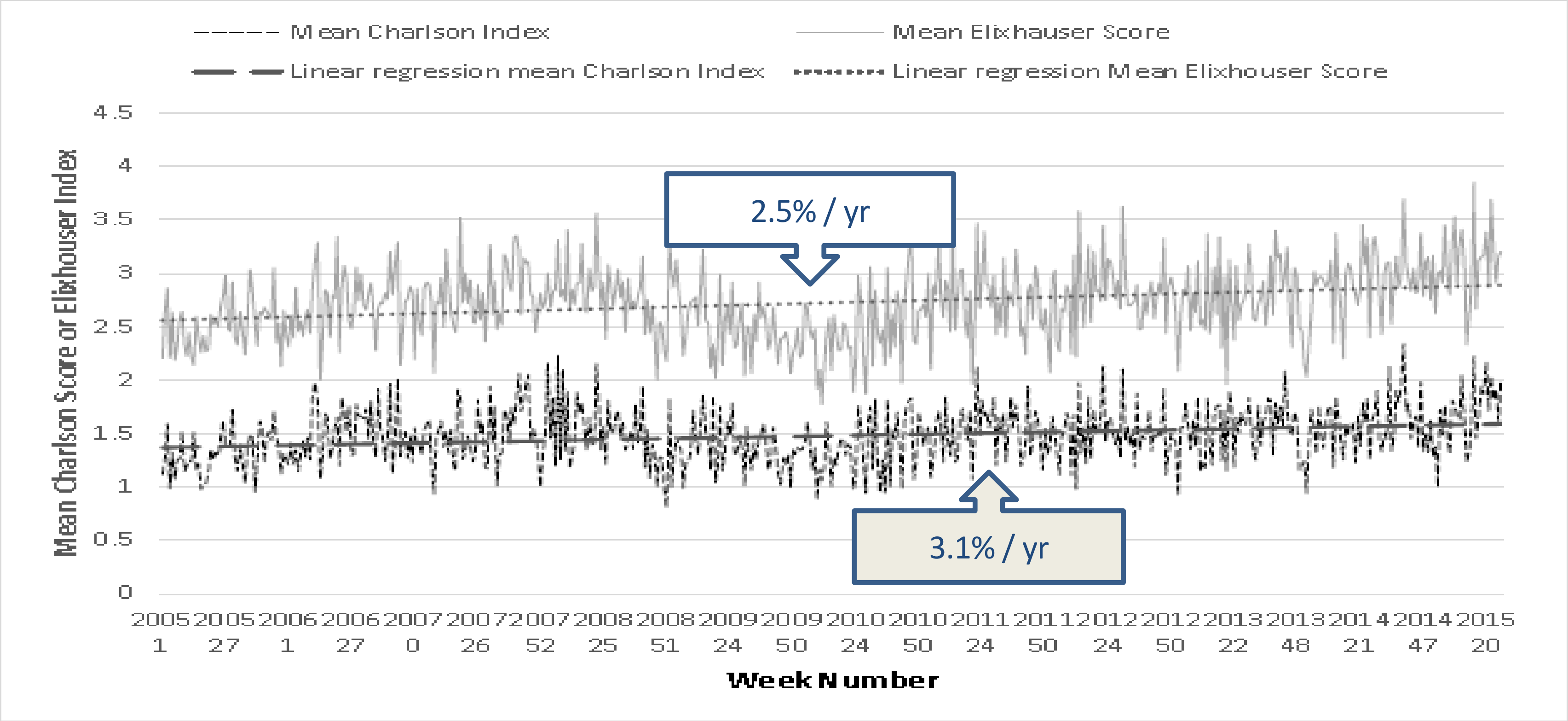
  0 = routine patient, no additional requirements

  1 = fall precautions

  2 = fall precautions + additional assistance (ambulation, re-orientation, nebulizer or medications)

  3= requires in - hospital study

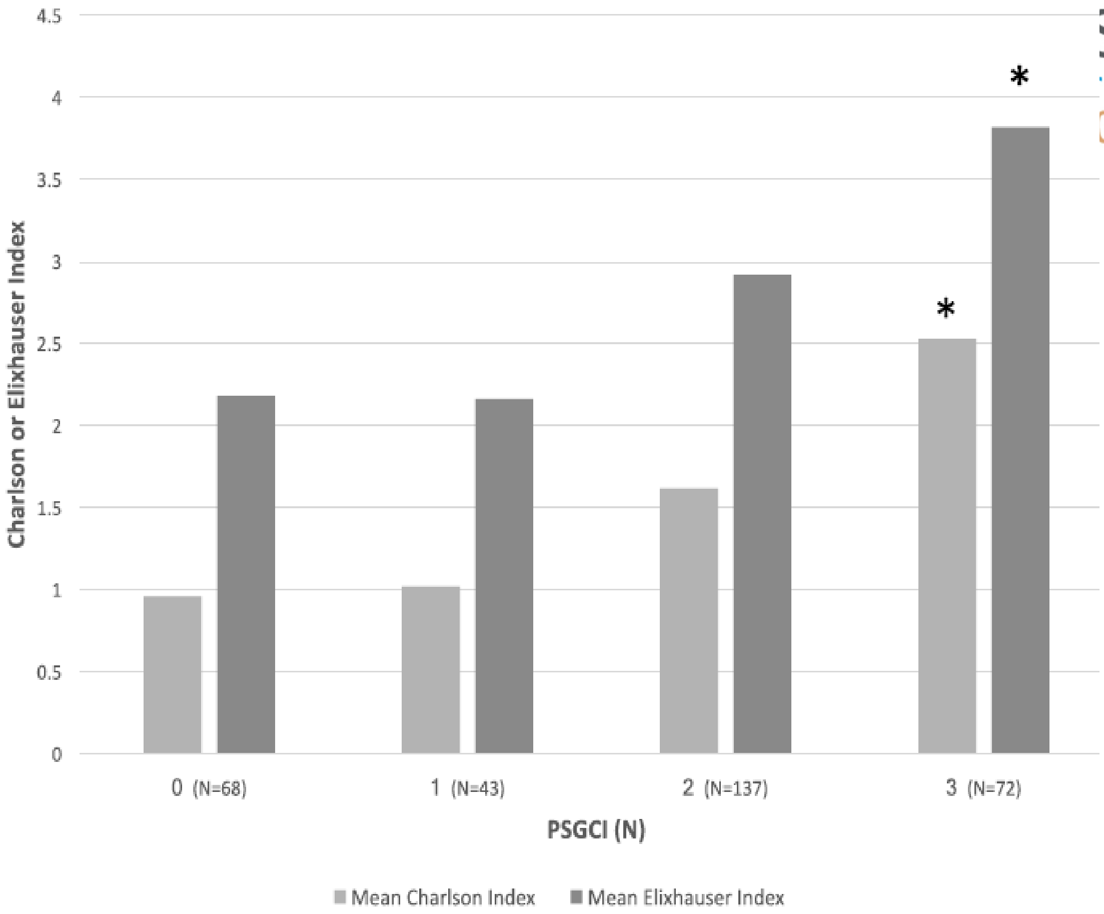
Figure 2: Slope of the Charlson Comorbidity and Elixhauser Index over a 10-year period



Analysis of the Complexity of Patient Undergoing Attended PSG in the Era of HSAT
Colaco B, et al. JCSM 2018; 14 (4): 631-640

- Overall volumes steady
- 30% increase in comorbidities
  - Differences persisted after adjustment for age, sex, BMI and race
- Pts were older, more female, lower BMI's
- Patients had more peripheral vascular disease, renal disease, liver disease, dementia, MI and hemiplegia (stroke)

- Sleep study complexity also increased


Charlson or Elixhauser Index
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
*
*
0 (N=68)
1 (N=43)
2 (N=137)
3 (N=72)
PSGCI (N)
Mean Charlson Index
Mean Elixhauser Index

Implications for the future

- Patients in sleep labs are sicker, less mobile and require more complex titrations
- Labs need to "gear up" for these types of patients – fall precautions, more sophisticated monitoring (CO2)
- Technologists need to become more knowledgeable about comorbid diseases
  - Peritoneal dialysis
  - LVAD's (left ventricular assist devices)
  - Continuous infusions
  - HGNS (hypoglossal nerve stimulators)
  - VNS (vagal nerve stimulators)

Conclusions

- The search for biomarkers continues and has great promise to assist with better phenotyping of our patients with sleep disorders
- Consumer sleep technologies are the future, better validation needed
- Beware the MSLT !!
- PSG patients are sicker and require higher intensity management