Supplementary Table 1 Comorbidities within the sample.								
Healthy		Mild		Moderate		Severe		
Comorbidity	Freq.	Comorbidity	Freq.	Comorbidity	Freq.	Comorbidity	Freq.	
asthma	1	DM2	1	asthma	1	asthma	1	
Brugada	1	Eagle's syndrome	1	DM2	1	atrial fibrillation	1	
syndrome								
COPD	3	IPB	1	RGE	1	COPD	1	
Henoch-	1	Kidney stone	1	arterial	5	DM2	4	
Schonlein		disease		hypertension				
purpura	1	abdominal cartia	1	hinalar dicardar	1	Nouropathy	1	
IPB	T	abuominal aonic	T	bipolar disorder	T	neuropatry	T	
nolvalohulia	1	adenoidectomy	1	dyslinidaemia	2	nolyneuronathy	1	
allergy	1	alleray	1	hyperprolactine	1	aortic sclerosis	1	
allergy	Ŧ	allergy	Ŧ	mia	Ŧ		Ŧ	
arterial	1	aortic sclerosis	1	psicosis	1	arterial	4	
hypertension						hypertension		
bruxism	1	arterial	6	rheumatoid	1	cholelithiasis	1	
		hypertension		arthritis				
cardiopathy	1	autism	1	thyroidectomy	1	chronic	1	
						respiratory		
aliu wa a l	2	hin class die ender	1			failure	1	
ulumai	Z	bipolar disorder	T			ulumai	T	
dizziness	1	breast carcinoma	1			diverticulosis	1	
extrasystole	1	chronic henatitis	1			dyslinidaemia	3	
aonarthrosis	1	diurnal somnolance	1			assential tromor	1	
bonatomogaly	1	ductinidaomia	1 2			byperuricomia	1	
histsl bornis	1	opilopov	2			ischomic	1	
malai nemia	T	epilepsy	T			cardionathy	T	
hypothyroidism	1	fibromvalgia	1			migraine	1	
meningioma	- 1	nhlebitis	- 1			nephrectomy	- 1	
migraine	- 1	hypothyroidism	- 1			nacemaker	- 1	
renal failure	1	memory	1			urinary tract	1	
	-	impairment	-			carcinoma	-	
		migraine	1			ventricular	1	
		C C				hypertrophy		
		Morton's neuroma	1					
		ophthalmopathy	1					
		pacemaker	1					
		paroxysmal	1					
		supraventricular						
		tachycardia	-					
		prostatic carcinoma	1					
		rneumatoid arthritis	1					
		tonsillectomy	2					
Supplementary Table 1 shows comorbidities' frequency in the sample, stratified by AHI severity class.								

Supplementary Figure 1. Contribution of each descriptor to algorithms' performance



Supplementary figure 1 depicts the contribution of each descriptor to sensitivity, specificity, and diagnostic odds ratio (DOR). The pairs of algorithms were retrained excluding during each training round one descriptor (along x axis). The procedure was repeated 5 t imes, one for each AHI<5 vs AHI \geq 5 (A), AHI<15 vs AHI \geq 15 (B), AHI<30 vs AHI \geq 30 (C), Mild vs Moderate -Severe (D) and Moderate vs Severe (E) classification. Sensitivity, Specificity and DOR were further reported in the case in which no descriptor was dropped (AII). A blue dotted line was added in each plot to better understand whether the algorithms achieved a better or worse performance if trained on a dataset having a dropped descriptor.

Supplementary Table 2 Patients' main characteristics								
Descriptor		Mean (sd)	r	p-value				
Age			0.161	0.158				
Gender	F	17.16 (17.41)		0.407				
	Μ	14.28 (14.28)						
BMI			0.230	0.042*				
Naw			0.106	0.358				
SFI			0.043	0.710				
mLaw			-0.021	0.858				
TST			-0.223	0.050*				
WASO			0.020	0.860				
SE			-0.133	0.245				
mHRs			0.117	0.306				
mHRw			0.033	0.773				
Dyslipidaemia	Yes	33.99 (28.78)		0.115				
	No	13.76 (12.82)						
DM2	Yes	36.25 (13.88)		0.103				
	No	13.96 (27.31)						
Hypertension	Yes	16.53 (11.28)		0.700				
	No	18.61 (21.82)						

The table shows the results of the correlations between AHI and the descriptors (i.e., age, BMI, Naw, SFI, mLaw, TST, WASO, SE, mHRs, mHRw), as well as the comparisons between mean AHI in groups identified by gender and comorbidity status. Only comorbidities present in more than five participants (i.e., dyslipidemia, type 2 diabetes mellitus, arterial hypertension) were included in the analysis. Pearson test was run to correlate AHI with quantitative variables, Student t test for group comparisons. AHI mean and standard deviation in each group and Pearson r coefficient are reported. BMI was positively correlated with AHI, while TST was found negatively correlated to AHI. No other p-values reached significance. P-value significance was set at 0.05.



Supplementary Figure 2 shows how the Matthews Correlation Coefficient (MCC) varies when a progressively larger number of samples is dropped from the training dataset. We progressively eliminated 0, 2, 5, 10, 15 and then 20 random samples from the dataset. This procedure was repeated 30 times The mean MCC was then calculated. Given that the performance is stable (i.e., a plateau was reached), we assume that a dataset comprised of 78 participants is large enough to be used for training our algorithms. This procedure was carried out on the algorithm applied to the AHI=5 threshold classification.