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ORIGINAL RESEARCH

Artificial Intelligence Screening Tool for Obstructive Sleep Apnoea: A Study Based on Outpatients at a Sleep Medical Centre

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Purpose: Due to the lack of clear screening guidelines for different populations, identify strategies for obstructive sleep apnea (OSA) in the outpatient population are unclear, a large number of potential OSA outpatients have not been identified in time. The purpose of our study was to evaluate the applicability and accuracy of artificial intelligence sleep screening in outpatients and to provide a reference for OSA screening in different populations.

Methods: A type IV wearable artificial intelligence sleep monitoring (AISM) device was used to screen adults in the sleep clinic of the Sleep Medical Center for OSA screening, and the general demographic data of the patients were collected. The epidemiological characteristics obtained by AISM screening were analysed. The accuracy of the AISM for the diagnosis of OSA was evaluated and compared with that of polysomnography (PSG).

Results: A total of 1492 participants completed all the studies. The data included 1448 cases total, including 1096 male patients and 352 female patients, with 620 of the total patients being overweight (42.82%) and 429 being obese patients (29.63%). The prevalence of males was 78.19%, and that of females was 55.97% ($\chi 2 = 95.72$, $P < 0.001$). In males, the risk of moderate to severe OSA was 74.21% in obese people, while in females, the risk was 50%. Age, body mass index (BMI) and the oxygen desaturation index (ODI) were positively correlated and negatively correlated with the lowest and mean oxygen saturation. A total of 100 participants completed both PSG and AISM monitoring, and the accuracies of the AISM in diagnosing mild and moderate-to-severe OSA were 94% and 98%, respectively.

Conclusion: The AISM exhibits good accuracy, and the use of an objective and convenient sleep detection device to screen a large sample population of outpatients is feasible. The prevalence of OSA in adults in sleep clinics is high, and age, sex, and BMI are risk factors for OSA.

Keywords: obstructive sleep apnoea, outpatient population, wearable artificial intelligence sleep monitor, epidemiological characteristics

Introduction

Sleep-disordered breathing (SDB) is a group of disorders characterized by abnormal breathing during sleep, with obstructive sleep apnoea (OSA) being the most prevalent disorder. Sleep apnoea and/or hypopnea caused by upper airway obstruction during sleep is usually accompanied by snoring, sleep structure disorders, intermittent hypoxia, daytime drowsiness, inattention and other symptoms. It can lead to hypertension, coronary heart disease, diabetes, metabolic syndrome, cognitive dysfunction and other multiorgan multisystem damage and a decrease in quality of life.[1,2] The prevalence of OSA has risen sharply worldwide; the number of global OSA patients has exceeded 936 million, and this number has reached 176 million in China. Unfortunately, it is generally believed that there is a high degree of underdiagnosis and treatment gap.[3]

In view of the high incidence rate of OSA and its significant impact on public health, an in-depth understanding of its epidemiological characteristics is particularly important.[4] However, although traditional sleep monitoring methods, such as polysomnography (PSG), are the gold standard for the diagnosis of OSA, their application in large-scale epidemiological studies is limited because of their high cost, limited equipment and inconvenient monitoring.[5,6] Subjective screening

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questionnaires, such as the STOP-Bang and the Berlin Questionnaire (BQ), which are easy to use, have low sensitivity and specificity, making them unacceptable screening options.[7]

In recent years, the rapid development of artificial intelligence (AI) technology has led to revolutionary changes in the field of health care, especially in the field of sleep health. AI algorithms have been proven to have great potential for analysing sleep patterns, identifying OSA and providing personalized treatment suggestions.[8] The AI-driven sleep screening tool provides a new perspective and tool for epidemiological research because of its low cost, high accessibility and user friendliness.[9,10]

The purpose of this study was to use AI technology to conduct adult OSA sleep screening in a sleep medical centre outpatient clinic, evaluate the applicability and accuracy of AI screening tools in identifying adult OSA patients, and analyse the epidemiological characteristics of adult OSA patients based on the screening results. To explore the applicability of AI screening in different populations and potential public health intervention strategies, and expect to provide more effective strategies for the early diagnosis, treatment and prevention of OSA.

Methods

Participants

The data of suspected OSA patients ≥ 18 years old were collected from March 1, 2022, to May 31, 2023, in the outpatient clinic of Wuhan Central Hospital Sleep Medicine Center, and artificial intelligence (AI) sleep screening was performed, including basic information such as birth date, sex, height, weight, and past disease history. The body mass index (BMI) (weight [kg]/height^2 [m^2]) was calculated for each participant. The study was conducted in accordance with the principles of the Helsinki Declaration and approved by the Ethics Committee of Wuhan Central Hospital (No.: WHZXKYL2022-045), informed consent was obtained from all individual participants included in the study. The exclusion criteria for patients were as follows: (1) had severe cardiac or pulmonary dysfunction or unstable nervous system disease; (2) had a mental illness and could not cooperate with the examination; and (3) had depression, anxiety or other mental disorders and were taking psychotropic drugs such as sedatives.

AI Sleep Monitoring

All the subjects used a portable artificial intelligence sleep monitor (AISM) (Chengdu Yunweikang Medical Technology Co., Ltd., Chengdu, China) as the objective method for evaluating the OSA. The monitoring sites were the palmar thenar major muscles, avoid veins, scars, and dense hair areas. This terminal features a patented design, with an overall size of merely 29×23×10mm and a weight of only 5.35g. The device uses a photoelectric reflector sensor to measure pulse oxygen saturation based on the absorption characteristics of hemoglobin under infrared and red light.[11] The monitoring time ranged from 23:00 at night to 6:00 the next morning, during which continuous monitoring and storage of three data (blood oxygen saturation, pulse rate, and movement), are automatically achieved. After the AISM patch recovered, based on physical activity signals, artifact identification, and built-in automated algorithms, the duration of effective monitoring and the number of oxygen saturation decreases (≥4%) were recorded and analyzed, the oxygen desaturation index (ODI), lowest blood oxygen saturation (LSaO2), mean oxygen saturation (MSaO2) and time when the blood oxygen saturation was less than 90% were automatically calculated through the built-in artificial intelligence system, and reports were generated automatically. On-site guidance, pictures and video materials were provided for the subjects to ensure the accuracy of wearing the device at home. The ODI obtained using the AISM was defined as a decrease in blood oxygen saturation of ≥4% and referred to as the total number of drops in oxygen saturation divided by the effective monitoring time.

PSG and OSA Diagnosis

A total of 100 participants underwent simultaneous overnight PSG and AISM sessions at the sleep centre, which were conducted by experienced technicians, starting at 23:00 and ending at 6:00 the next day, to assess the sensitivity and specificity of the AISM for the diagnosis of OSA. PSG (Alice6, Philips Respironics Inc., USA) recorded electroencephalogram (EEG), eye movement, mandibular electromyography (EMG), electrocardiogram (ECG), oral and nasal airflow, chest and abdomen movement, snoring, blood oxygen saturation and other indices at the same time. The results were interpreted manually by physicians trained in sleep medicine in accordance with the American Academy of Sleep Medicine (AASM) standards on the Interpretation of Sleep and Related Events.[5] The apnoea–hypopnea index (AHI) was defined as the sum of the average number of apnoea and hypopnea episodes per hour during sleep. The severity of OSA was defined as follows: mild, 5 events/h≤ODI<15 events/h; moderate, 15 events/h≤ODI<30 events/h; and severe, ODI≥30 events/h. The severity of $LSaO_2$ was as follows: mild, 85%≤$LSaO_2$<90%; moderate, 80%≤$LSaO_2$<85%; and severe, $LSaO_2$<80%. The sensitivity, specificity, positive predictive value, negative predictive value and accuracy of the AISM ODI were calculated by using the thresholds of AHI≥5 events/h, ≥15 events/h and ≥30 events/h obtained from the PSG.

Statistical Analysis

The data were analysed using SPSS 23.0 software (IBM SPSS 23.0, Armonk, NY, USA). Descriptive statistics were used. Continuous variables with a normal distribution are expressed as the mean ± standard deviation, and categorical variables are expressed as frequencies and percentages. Student's *t* test was used for continuous variables with a normal distribution, and one-way analysis of variance (ANOVA) was used for categorical variables. The risk factors affecting OSA were analysed by the Spearman correlation coefficient. Receiver operating characteristic (ROC) curves were used to evaluate the accuracy of the AISM in diagnosing OSA.

Results

Participant Characteristics

Table 1 shows that a total of 1492 people participated in the screening, and 1448 valid analytical data points were obtained, for an effective rate of 96.1%. Age group definition:Youth: 18–35 years old; Middle age: 36–59 years old; Old age≥60 years old.There were 1096 males with an OSA incidence of 78.19% and 352 females with a prevalence of 55.97% ($\chi2$=95.72, P<0.01), with a predominance of male patients and a statistically significant difference between the sexes. The proportion of overweight individuals was 42.81% (620/1448), and that of obese individuals was 34.46% (499/1448).

Table 1 Characteristics of the Study Participants

Characteristic	Mean ± SD or n (%)
Number of screenings	1492
Valid data	1448
Male	1096
Age (years)	42.3±15.8
BMI (kg/m^2)	26.3±4.0
OSA	857 (78.2)
Female	352
Age (years)	45.7±19.7
BMI (kg/m^2)	24.2±5.1
OSA	197 (55.9)
BMI (kg/m^2)	
Normal	22.1±1.4(399)
Overweight	25.8±1.2(620)
Obesity	30.9±2.8(499)
Age	
Youth	29.5±4.3 (444)
Middle age	46.9±7.1 (742)
Old age	69.0±8.5 (252)

Notes: BMI standards: normal, 18.5 kg/m^2≤BMI<24 kg/m^2; overweight, 24.0 kg/m^2≤BMI<28.0 kg/m^2; and obesity, BMI≥28.0 kg/m^2. Age Group: Youth: 18–35 years old; Middle age: 36–59 years old; Old age≥60 years old.
Abbreviation: BMI, body mass index.

Distribution of OSA Severity

Among the different age groups, the highest proportion of patients with OSA was found in the middle-aged group (80.79% for males, 58.46% for females). In the elderly group, the proportion of patients with OSA was also relatively high (79.01% for males, 65.56% for females). This suggests that the increase in age may be related to the increase in OSA incidence. Among all BMI groups, the obese group had the highest proportion of patients with OSA (88.98% for males, 76.92% for females). The results of the analysis of variance showed that age and BMI classification had a significant influence on the ODI (F=9.727, F=113.92, P<0.001), which indicated that there were significant differences in the ODI among individuals of different age groups and BMI classifications, as shown in Table 2 and Figure 1.

Distribution of Hypoxia Severity

In males, the proportion of severe hypoxia risk was highest (51.00%), while in females, the proportion of mild risk was highest (32.83%). The severity of hypoxia in males was greater than that in females, suggesting that sex affects the severity of hypoxia. Among obese people, the risk of severe hypoxia was the highest (64.10%), which was much greater than that of normal (33.83%) and overweight (44.35%) individuals. The results of analysis of variance showed that age had no significant effect on LSaO2 (F=1.949, P>0.05); BMI classification had a very significant effect on LSaO2 (F=59.11, P<0.001), as shown in Table 3 and Figure 2.

Analysis of the Correlation Between Oxygen Saturation or ODI and Age or BMI

Spearman correlation analysis revealed that age and BMI were negatively correlated with $MSaO_2$ (−0.20, −0.40, P<0.001) and $LSaO_2$ (−0.16, −0.39, P<0.001), indicating that the older the age and the greater the BMI were, the lower the blood oxygen, while age and BMI were positively correlated with the ODI (0.19, 0.47, P<0.001), indicating that the greater the age and BMI were, the greater the ODI was, and the correlation of BMI was stronger than that of age.

Table 2 Distribution of OSA Severity According to Sex, Age, and BMI

Characteristics	Severity of OSA			
	Non-OSA	Mild	Moderate	Severe
Sex				
Male (n,%)	239(21.8)	305(27.8)	210(19.2)	342(31.2)
Youth	98(25.9)	116(30.8)	64(16.9)	99(26.3)
Middle age	107(19.2)	140(25.1)	114(20.5)	196(35.2)
Old age	34(21.0)	49(30.3)	32(19.8)	47(29.0)
Female (n,%)	155(44.0)	107(30.4)	44(12.5)	46(13.1)
Youth	43(64.2)	17(25.4)	6(9.0)	1(1.5)
Middle age	81(41.5)	60(30.8)	22(11.3)	32(16.4)
Old age	31(34.4)	30(33.3)	16(17.8)	13(14.4)
BMI (n,%)				
Normal	181(45.4)	120(30.1)	46(11.5)	52(13.0)
Overweight	165(26.6)	193(31.1)	119(19.2)	143(23.1)
Obesity	48(11.2)	99(23.1)	89(20.8)	193(45.0)

Notes: ODI thresholds for OSA severity: mild: 5 events/h≤ODI<15 events/h, moderate: 15 events/h≤ODI<30 events/h, severe: ODI≥30 events/h.
Abbreviations: BMI, body mass index; ODI, oxygen desaturation index.

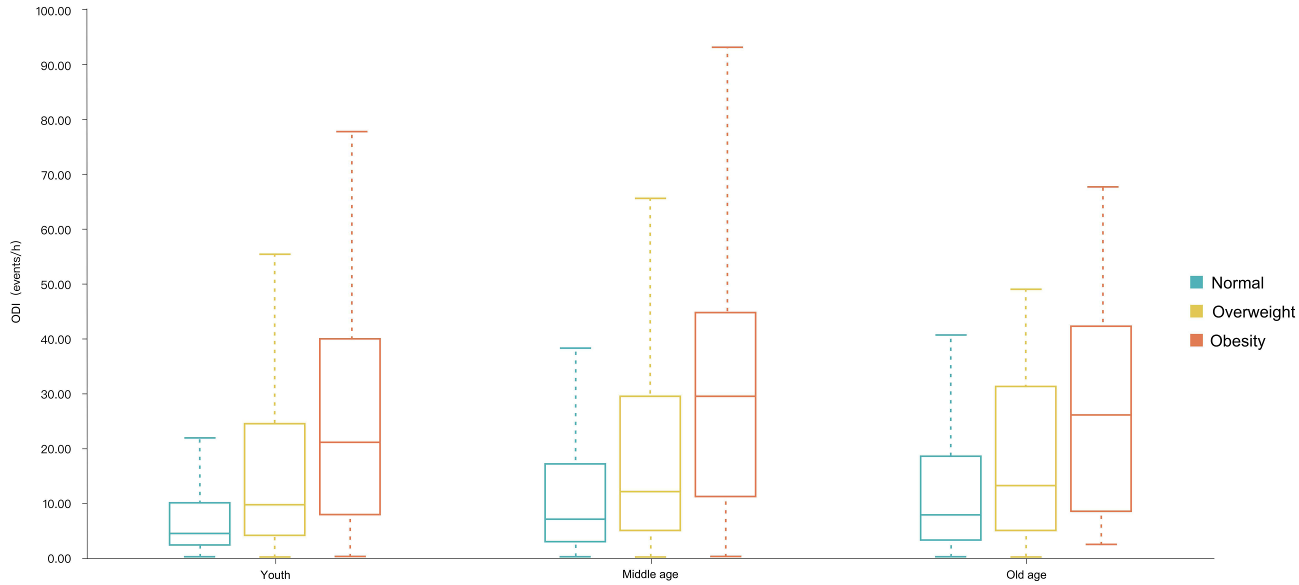

Figure 1 Age group, BMI and ODI. The results of the analysis of variance showed that age and BMI classification had a significant influence on the ODI, which meant that there were significant differences in the ODI among individuals of different age groups and BMI classifications.
Abbreviations: BMI, body mass index, ODI, oxygen desaturation index.

Analysis of the Accuracy of the AISM in Diagnosing OSA

A total of 100 participants completed both PSG and AISM. According to the PSG results, 25 patients had mild OSA, 29 patients had moderate OSA, and 25 had severe OSA. Table 4 shows the sensitivity, specificity, positive predictive value, negative predictive value, and accuracy of the AISM in diagnosing OSA at the ODI≥5, ≥15 and ≥30 thresholds compared with those of PSG. The sensitivities were 94%, 96% and 92%, the specificities were 95%, 100%, and 98%, and the accuracies were 94%, 98%, and 97%, respectively. When an AHI ≥5 events/h was used as the criterion for diagnosing OSA, the area under the ROC curve was 0.976 (P<0.001, 95% confidence interval [CI]=0.949,1.000). When the AHI was

Table 3 Distribution of $LSaO_2$ Severity According to Sex, Age, and BMI

Characteristics	Severity of $LSaO_2$			
	Normal	Mild	Moderate	Severe
Sex				
Male (n,%)	47 (6.2)	194(19.0)	272(23.8)	583(51.0)
Youth	20(5.3)	75(19.9)	94(24.9)	188(49.9)
Middle age	22(3.9)	87(15.6)	133(23.9)	315(56.6)
Old age	5(3.1)	32(19.8)	45(27.8)	80(49.4)
Female (n,%)	35(14.4)	109(32.8)	106(26.8)	102(26.0)
Youth	12(17.9)	25(37.3)	14(20.9)	16(23.9)
Middle	7(8.7)	63(32.3)	53(27.2)	62(31.8)
Old age	6(6.7)	21(23.3)	39(43.3)	24(26.7)
BMI (n,%)				
Normal	39(9.8)	117(29.3)	108(27.1)	135(33.8)
Overweight	30(4.8)	138(22.3)	177(28.6)	275(44.4)
Obesity	13(3.0)	48(11.2)	93(21.7)	275(64.1)

Notes: The severity of $LSaO_2$ was as follows: normal: $LSaO_2$≥90%; mild: 85≤$LSaO_2$ <90%; moderate: 80%≤$LSaO_2$<85%; and severe: $LSaO_2$<80%.
Abbreviations: BMI, body mass index;$LSaO_2$,Lowest blood oxygen saturation.

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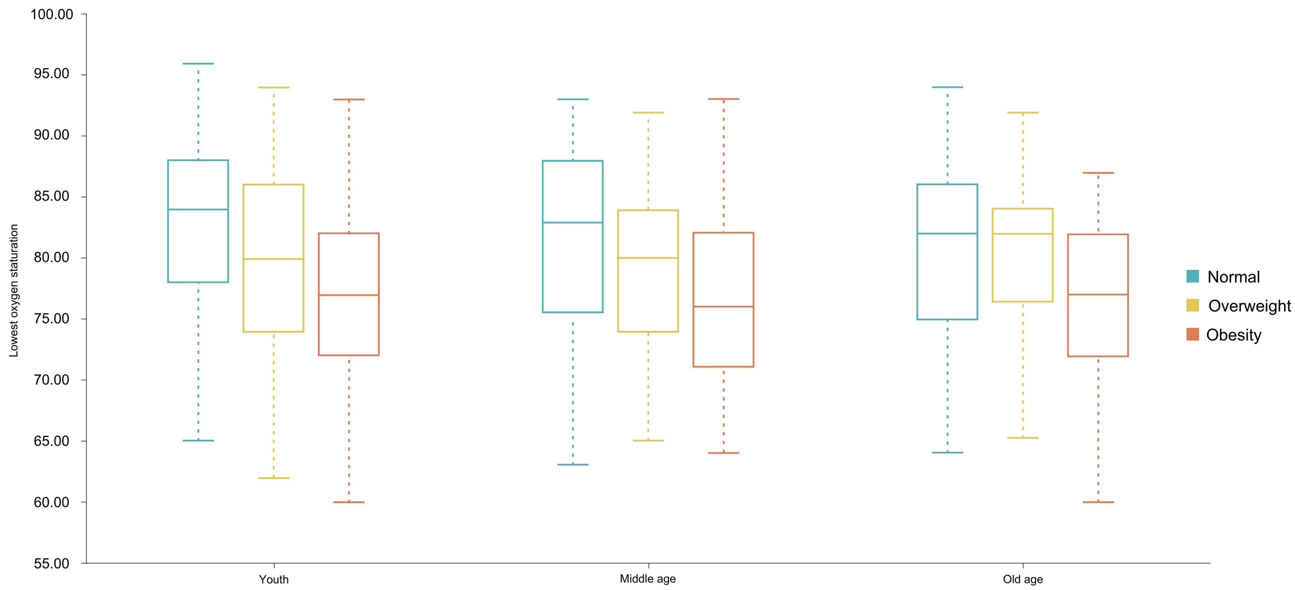

Figure 2 Age group, BMI and $LSaO_2$.The results of analysis of variance showed that age had no significant effect on the $LSaO_2$; BMI classification had a very significant effect on the $LSaO_2$.
Abbreviations: BMI, body mass index; $LSaO_2$, Lowest blood oxygen saturation.

≥15 events/h or ≥30 events/h, the area under the ROC curve was 0.992 (P<0.001, 95% CI=0.978,1.000) or 0.984 (P<0.001, 95% CI=0.955,1.000), respectively (Figure 3).

Discussion

OSA has serious impacts on individual health, leading to significant economic and social burdens, and has become an important public health issue that cannot be ignored globally.[3,12] However, there is a low level of awareness about OSA, and data show that even in developed countries, the majority of OSA patients remain undiagnosed and untreated. The complexity of treatment and management significantly increases when the disease progresses to the stage of complications. Therefore, early diagnosis and timely intervention for OSA are crucial.[13] Although PSG is the gold standard for the diagnosis of obstructive sleep apnoea syndrome, it is associated with high technical requirements, tedious operation, and other reasons, resulting in a long waiting time and poor patient compliance, rendering it unsuitable for large-scale screening of patients in the general population.[5,6] For the large number of suspected OSA patients attending the sleep centre outpatient clinic, we used the AISM for screening. An AISM is a compact device with no external wires and can be easily connected to one's palm in just one step. The lower application difficulty ensures the convenience, completeness, and effectiveness of data collection.[14] The data efficiency of our application of this device is 97.1%, which is better than that of previous research results, in which between 5% and 20% of the data in portable studies were of poor quality.[15] To analyse the reasons for this difference, we benefitted from the convenience of equipment operation, and on the basis of on-site guidance, we also provided pictures and video materials to help the subjects view the wearing methods and matters needing attention at any time to ensure the integrity of equipment recovery and the validity of the

Table 4 Analysis of the Accuracy of AISM in Diagnosing OSA

Screening Threshold	Participants	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Accuracy (%)
ODI≥5 events/h	75	94	95	98	80	94
ODI≥15 events/h	52	96	100	100	96	98
ODI≥30 events/h	24	92	99	96	97	97

Abbreviations: AISM, artificial intelligent sleep monitor; ODI, oxygen desaturation index; PPV, positive predictive value; NPV, negative predictive value.

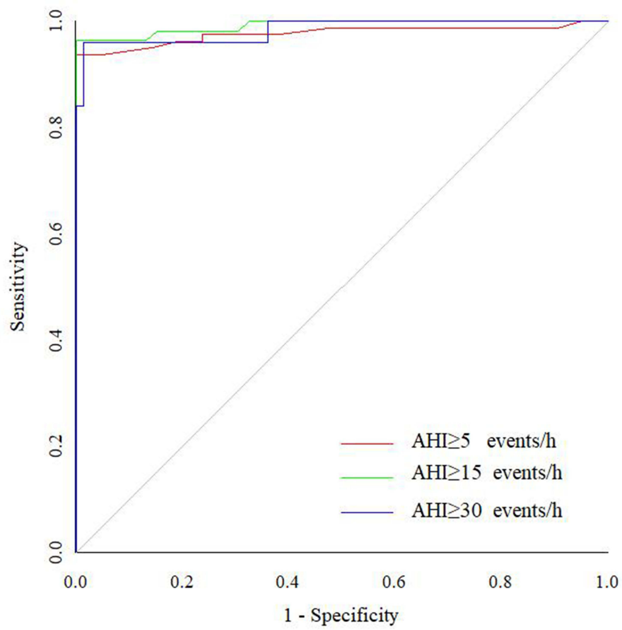

Figure 3 ROC curves for OSA diagnosis using the AISM.
Abbreviations: ROC, receiver-operating characteristic; AISM, artificial intelligent sleep monitor; AHI, apnea–hypopnea index.

data. The results of our study show that among the suspected patients with sleep-disordered breathing treated at this centre, 78.19% were males and 55.97% were females, with a male predominance, consistent with the results of an epidemiological study of 8037 patients diagnosed with sleep disorders by PSG at a single centre.[16] In patients treated at sleep centres, the male-to-female ratio is between 8:1 and 10:1, and the prevalence of OSA in men is significantly greater than that in women.[17] The difference in OSA incidence between men and women may be related to sex differences in development, hormone levels, upper airway anatomy, fat distribution and respiratory stability.[18] Among general adults, the prevalence of OSA is 14% in males and 5% in females.[19] An epidemiological study on the Chinese community population suggested that the prevalence of obstructive sleep apnoea (OSA) in adults in the community was 30.7%.[20] Considering that the population of interest in this study consisted of patients visiting sleep medicine centres, the prevalence of OSA was significantly greater than that of the general population. Therefore, it is necessary to conduct early screening in a large number of patients in sleep clinics.

Our research showed that BMI had significant effects on the $LSaO_2$ and ODI, with significant differences in these indices among the different BMI groups. The obese group had the highest percentage of patients with OSA, suggesting that obesity is an important risk factor for OSA. Epidemiological studies revealed that the prevalence of OSA reached 44.6% in middle-aged men and 13.5% in women with a BMI between 30 and 40 kg/m^2.[19] In our study population of sleep clinic patients, 74.21% of the males in the obese group had moderate to severe OSA, and 50% of the females in the obese group had OSA. Compared with Caucasians, Chinese individuals, due to factors such as craniofacial structure, experience a significantly greater impact of BMI increase on the severity of OSA, with a steeper increase in the AHI as BMI increases.[21] Obesity, especially central obesity, and increased BMI are usually associated with increased body fat mass, especially fat accumulation around the neck, including an increase in the thickness and volume of soft tissue in the pharynx, which can reduce the upper airway. These changes may lead to or exacerbate airway obstruction during sleep, thereby increasing the risk of OSA.[22,23] Our previous research also suggested that effective weight management combined with uvulopalatopharyngoplasty can improve long-term treatment outcomes for obese-related OSA patients, and weight loss is an important part of treatment for OSA patients with a high BMI.[24] BMI is an important risk factor for OSA. Monitoring and managing BMI can effectively identify high-risk populations for OSA and formulate personalized prevention and treatment strategies. This study suggested that the risk of OSA increases with age and that age is negatively correlated with average blood oxygen and the lowest blood oxygen levels. However, in the elderly group, the

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proportion of patients with severe hypoxia and severe ODI decreased. These results indicate that as age increases, the prevalence of OSA increases but the severity decreases, which is similar to related research.[25] Although the exact mechanism leading to an increase in the prevalence of OSA in elderly individuals has yet to be fully understood, several potential contributing factors have been identified, including age-related narrowing of the upper airway, decreased upper airway muscle tone, reduced lung capacity, changes in hormone levels, increased frequency of arousals, and decreased stability of respiratory control.[26]

To verify the screening effect of IV-type AISM in a large population of sleep centre outpatients, 100 participants were selected for simultaneous overnight PSG monitoring. Our research indicated that the AISM exhibits high sensitivity and specificity. The sensitivities of the AISM for diagnosing mild, moderate and severe OSA were 82.14%, 90% and 96%, respectively; the specificities were 80.64%, 88.57%, and 92.30%, respectively; and the accuracies were 90%, 93%, and 95%, respectively. With increasing disease severity, sensitivity, specificity, and accuracy, the diagnostic accuracy of the AISM for moderate and severe OSA was significantly greater than that for mild OSA. This may be related to the definition of the oxygen reduction index and apnoea hypopnea index; apnoea may not be associated with a decrease in blood oxygen saturation, while hypopnea is accompanied by a decrease in blood oxygen saturation or microarousal.[5] In addition, the ODI is defined as the ratio of the number of times oxygen saturation decreases from baseline to the effective monitoring time, instead of sleep time as the denominator, and may underestimate the condition of OSA patients. Therefore, it is recommended that AISM be diagnosed as negative, but patients with symptoms of OSA should undergo monitoring with PSG. Some studies have demonstrated a strong correlation and consistency between the ODI obtained by type IV AISM and the AHI derived from PSG, indicating that type IV AISMs exhibit commendable diagnostic efficacy as a screening tool.[14,20] Compared with traditional finger-clip or ring-type pulse oximeter, this monitoring terminal can significantly enhance wearing comfort and adaptability, minimize the impact of light leakage, body movement, and finger size differences on data quality, thereby improving data quality. Among the artificial intelligence algorithms, there are multiple algorithm systems that have already obtained Chinese invention patents, including the blood oxygen segmentation algorithm based on U-Net,[27] etc. The blood oxygen segmentation algorithm can more effectively filter out spurious data to enhance the data quality used for calculating parameters such as ODI, thereby attaining diagnostic performance that is significantly superior to similar tools. Our research results show that AISM equipment has the advantages of small size, high sleep comfort, and simple operation but is highly accurate, so it is highly acceptable and accessible to patients. Of course, more studies are needed to verify the accuracy and effectiveness of AI screening tool.

This study validated the accuracy of the type IV AISM sleep screening device for the diagnosis of adult OSA. It continuously monitors signals such as blood oxygen saturation and heart rate in the human body through its artificial intelligence algorithm and calculates the ODI through its own software for statistical analysis. The ODI is also the core monitoring index of PSG. In our study, the ODI was used to screen suspected OSA patients in outpatient clinics and has been indicated to be a useful tool for screening, diagnosing, and quantifying OSA.[28] AI screening is a convenient and efficient OSA screening tool, and previous studies have confirmed that it can be popularized and applied in community health service centres, outpatient clinics, and health management centres.[20] For certain specific populations, such as drivers and pilots who require high levels of alertness in their professions, AI screening can be incorporated as part of routine health assessments.[29] Early screening of high-risk populations can help improve the diagnosis and treatment rate of OSA, making early intervention possible and reducing the risk of related complications. In addition, AI screening can achieve remote diagnosis and personalized treatment, reduce medical costs, and improve patients' quality of life.[30] AI screening technology has great potential in the diagnosis and management of OSA, especially because of its applicability across different populations and its contribution to public health intervention strategies.[13] However, to achieve these potential advantages, more studies are needed to verify the accuracy and effectiveness of AI screening tools, and appropriate policies and guidelines need to be developed to support and guide their application in clinical practice. In addition, issues such as data privacy and information security need to be considered to ensure the widespread acceptance and effective implementation of AI screening tools.

In conclusion, this study confirmed the better applicability of using the AISM for large-sample screening in sleep clinics and revealed that the AISM exhibited good accuracy compared to PSG. The prevalence of OSA in adults in sleep clinics is high, and it is necessary to conduct early screening in this population to achieve early diagnosis and treatment of OSA. However, the device is unable to differentiate between obstructive and central sleep apnea, and also unable to facilitate the real-time remote transmission of monitoring data. Therefore further research and development of devices equipped with these functionalities is required in the future. More studies are needed to verify the accuracy and effectiveness of AI screening tool, and more studies may focus on evaluating AISM performance in healthy community peoples and health management centres.

Data Sharing Statement

The detailed participant data are available from the corresponding author upon reasonable request.

Ethics Approval

The study was conducted in accordance with the tenets of the Declaration of Helsinki. Ethical approval for this study was obtained from the ethics committee of Central Hospital of Wuhan (No.: WHZXKYL2022-045).

Informed Consent

All participants signed ethics committee-approved consent forms prior to participation.

Author Contributions

All authors contributed to the study conception and design. Jian Tan: designed and conducted comprehensive research, encompassing the planning, implementation, and analysis of the study, as well as the writing of the manuscript; Wei Chen: offered research guidance and manuscript revision. Tiantian Peng and Cheng Li: were responsible for data collection and organization; Dan Yu: performed data analysis, provided statistical software, and organized the charts; Kai Lv: implemented patient sleep monitoring and conducted the analysis of the monitoring data. All authors took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest.

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