Accuracy of Smartphone Application Screening for Obstructive Sleep Apnea in Chinese Adults

by

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Thesis submitted in partial fulfillment of
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ABSTRACT

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Abstract

Background: Obstructive Sleep Apnea-Hypopnea Syndrome (OSAHS) is a common sleep disorder affecting millions of adults worldwide, with a higher prevalence reported in Asia than in Western countries. If left untreated, OSAHS can lead to serious health complications such as high blood pressure, heart disease, stroke, and diabetes. While polysomnography (PSG) is considered the gold standard of sleep testing, it may not be suitable for all OSAHS patients due to its cost and invasiveness. In recent years, the development of mobile applications has provided a convenient and accessible tool for screening and diagnosing OSAHS. This study aimed to evaluate the accuracy of the Dr. Being app, an OSAHS screening software for smartphones, in analyzing Chinese adults for OSAHS. The findings of this study will provide insights into the potential of mobile health technologies in improving the detection and management of OSAHS in Asia.

Methods: In this prospective study conducted between December 2021 and December 2022, 50 patients were recruited from the Shanghai Sixth People's Hospital sleep center. Each participant underwent monitoring throughout the night using both the Dr. Being app and polysomnography (PSG). The Dr. Being app's automatic analysis generated relevant indicators, which were then compared with the results obtained from PSG interpreted by OSHAS clinicians according to recommended guidelines. The study aimed to evaluate the concordance between the apnea-hypopnea index (AHI) obtained by the Dr. Being app and PSG results. Furthermore, the researchers assessed the sensitivity and specificity of the Dr. Being app in diagnosing OSAHS, which could provide valuable insights into the effectiveness of smartphone apps in sleep testing.

Results: The study participants had a mean age of 48.6±16.2 years, a male predominance of 72%, and a mean body mass index of 28.8±4.0 kg/m^2. This study's findings suggest significant differences between the total sleep time (TST) and apnea-hypopnea index (AHI) measured by the Dr. Being app and PSG. Specifically, the TST measured by the Dr. Being app was significantly higher than PSG, while PSG had a slightly higher AHI measurement than the Dr. Being app. Despite these differences, the Bland-Altman consistency test showed that the AHI measurements obtained from both methods were statistically consistent, indicating that the Dr. Being app can provide accurate measurements of mild AHI. Furthermore, the study assessed the sensitivity and specificity of the Dr. Being app in diagnosing OSAHS at different AHI thresholds. The results indicated that the app had high sensitivity and accuracy for OSAHS diagnosis at an AHI threshold of 5/h and moderate sensitivity and specificity at an AHI threshold of 15/h. However, the sensitivity decreased while the AHI threshold increased to 30/h.

Conclusion: These findings highlight the usefulness of the Dr. Being app in the screening and diagnosing of OSAHS, particularly in resource-limited

areas where access to PSG may be limited. The app's high sensitivity in detecting early OSAHS indicates its potential as a valuable tool for clinicians and Chinese patients. Therefore, Dr. Being app has the potential to supplement traditional OSAHS diagnosing methods for clinicians and patients, thereby improving the accessibility and affordability of early detection and management of OSAHS, particularly among Chinese adults.

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1. Introduction

Obstructive Sleep Apnea Hypopnea Syndrome (OSAHS) is a prevalent sleep disorder characterized by recurrent episodes of complete or partial upper airway obstruction during sleep, leading to periodic breathing cessation and decreased blood oxygen saturation(1). Individuals with complete obstruction of the respiratory during sleep may experience interrupted sleep with frequent awakenings and loud snoring, which can lead to daytime sleepiness, fatigue, headache, impaired attention, depression, and sexual dysfunction(2). The prevalence of OSAHS varies across different regions of the world. In Western countries, the prevalence of OSAHS ranges from 5% to 30% in men and 2% to 15% in women(3), depending on the criteria used to define the disorder and the population studied. For example, a study conducted in the United States reported a prevalence of 24% in men and 9% in women based on an apnea-hypopnea index (AHI) of ≥ 5 events per hour, while another study from Spain reported a prevalence of 49.1% in men and 23.4% in women based on an AHI of ≥ 15 events per hour(4).

In Asia, the prevalence of OSAHS is reported to be higher than in Western countries, with estimates ranging from 10% to 40% in men and from 3% to 15% in women(5). A study conducted in China reported a prevalence of 22.2% in men and 8.1% in women based on an AHI of ≥ 5 events per hour(6). In Japan, the prevalence of OSAHS is estimated to be around 5% to 10% in men and about 2% to 5% in women(7). However, the prevalence of OSAHS in Asia may be underestimated due to cultural differences in the perception of sleep disorders and the low awareness of the condition among healthcare professionals.

In Africa, the prevalence of OSAHS is not well established due to the lack of studies on this topic. However, a few studies conducted in South Africa have reported a prevalence of 4.2% to 17.8% based on an AHI of ≥ 5 events per hour(8). In Latin America, the prevalence of OSAHS is reported to be similar to that in Western countries, with estimates ranging from 5% to 30% in men and from 2% to 15% in women(9). A study conducted in Brazil reported a prevalence of 32.8% in men and 17.5% in women based on an AHI of ≥ 5 events per hour(10).

Cumulating evidence suggests that OSAHS has been associated with numerous comorbidities, including hypertension, cardiovascular disease, diabetes mellitus, chronic obstructive pulmonary disease (COPD), and stroke, which significantly impact patient morbidity and mortality(11). Men are also more likely to develop OSAHS than women; although the gender gap narrows after menopause, early detection and intervention are critical to improve patient outcomes and prevent the development of comorbidities. Nevertheless, while OSAHS is a common condition, it is often undiagnosed. There are several reasons for this: 1. lack of awareness: many people are unaware that they have sleep apnea. They may not recognize the symptoms, or they may not think their symptoms are severe enough to seek medical attention; 2. Misdiagnosis: Sleep apnea can be mistaken for other conditions, such as snoring or insomnia; this can make it difficult to diagnose the condition correctly; 3. fear of diagnosis: Some people may be afraid to get tested for sleep apnea because they are worried about the results or the treatment options; 4. limited access to testing: Sleep apnea testing can be expensive and may not be covered by insurance, this can make it difficult for some people to get tested; 5. lack of symptoms during doctor visits: Sleep apnea symptoms may not occur during a doctor's visit, making it difficult for a doctor to diagnose the condition. Patients ultimately suffer from various irreversible OSAHS complications, such as hypertension, stroke, and impaired cognitive function(12).

Polysomnography (PSG) is the gold standard of OSAHS testing because it provides the most comprehensive evaluation of a patient's sleep patterns and can accurately diagnose various sleep disorders(13). PSG measures multiple physiological parameters during sleep, including brain waves, muscle activity, eye movement, heart rate, blood oxygen levels, and respiratory effort (14). By monitoring these parameters simultaneously, PSG can provide a detailed picture of the patient's sleep architecture, including the duration and quality of different sleep stages and any disruptions in breathing or other physiological processes(15). Because PSG can provide such a comprehensive evaluation of a patient's sleep, it is particularly useful for diagnosing complex sleep disorders, such as sleep-related movement disorders, parasomnias, and circadian rhythm disorders, as well as more common conditions, such as obstructive sleep apnea(16). PSG is also useful for monitoring treatment efficacy, as it can track changes in a patient's sleep patterns over time. In addition to its diagnostic and monitoring capabilities, PSG is also able to identify other factors that may be affecting a patient's sleep, such as periodic limb movement disorder, sleep-related seizures, or REM sleep behavior disorder(17). These data can be helpful in developing a treatment plan that addresses the patient's underlying sleep issues.

While PSG is considered the gold standard of sleep testing(19), it has limitations. PSG can be expensive and time-consuming, requiring specialized equipment and trained personnel to administer and interpret the results. Additionally, PSG may not be suitable for all patients, particularly those with difficulty sleeping in a clinical setting or mobility issues that make it difficult to attach the necessary sensors. Therefore, OSAHS diagnosis and management remain a challenge, and several diagnostic tools and treatment options are available to clinicians.

Home sleep tests (HSTs) have been shown to be a reliable and effective alternative to in-laboratory polysomnography (PSG) for the diagnosis of obstructive sleep apnea in certain patients(20). They are typically more convenient and less expensive than PSG, as they can be performed in the patient's home and do not require a trained technician to be present throughout the night. HSTs typically use smaller sensors attached to the patient's body, and the data is collected through a portable device that the patient can easily wear while sleeping. However, there are some limitations to HSTs that should be considered. While they can accurately diagnose obstructive sleep apnea, they may be less effective in detecting other sleep disorders or more complex cases of sleep apnea.

Additionally, the results of an HST may be affected by factors such as the patient's sleeping position, body position, or sleep quality, which can lead to inaccurate results. In some cases, a PSG may still be necessary to provide a more comprehensive evaluation of a patient's sleep disorder. The decision to use an HST or PSG will depend on the patient's needs and the specific details of their sleep disorder(21).

In the last few years, the percentage of mobile phone users worldwide has increased tremendously, from 45% in 2016 to 86% in 2022 (22). The widespread use of mobile phones has also increased the availability and accessibility of digital health services. Telemedicine, using technology to provide healthcare services remotely, has become increasingly popular in different parts of the world in recent years, particularly in response to the COVID-19 pandemic(23). Many health-related companies saw the opportunity of telemedicine and digitized their products and services, such as standard health analysis or assessment tests in a mobile app, to promote and track smartphone users' well-being daily or periodically. There are 350,000 health-related apps that users can select from their mobile app stores (24).

According to a report by McKinsey & Company, the use of telehealth services surged in the United States in 2020, with virtual care visits accounting for more than 20% of all medical visits by the end of the year. This represents a significant increase from the pre-pandemic period, when virtual care visits accounted for less than 1% of all medical visits(25). In many parts of Asia, telemedicine is seen as a way to improve access to healthcare in rural areas, where there are often shortages of healthcare providers and limited infrastructure to support in-person visits(26).

Telemedicine is also gaining popularity in China, particularly after the COVID-19 pandemic. According to a report by the China Internet Network Information Center, the number of online medical consultations in China increased by more than 30% in the first quarter of 2020 compared to the same period the previous year. The Chinese government has also launched several initiatives to support the development of telemedicine, including establishing telemedicine centers in rural areas and promoting mobile health apps(27).

The use of mobile health (mHealth) technology has made it possible for patients to receive remote care and consultations with healthcare providers through telemedicine, reducing the need for physical visits to clinics or hospitals. It also improved access to care, reduced costs, and increased patient convenience. However, there are also challenges associated with implementing telemedicine, such as concerns about patient privacy and the need for robust technological infrastructure to support virtual care(28). Despite challenges, the increasing popularity of telemedicine has emerged as a promising tool for OSAHS screening and diagnosis due to its convenience, accessibility, and cost-effectiveness.

The American Academy of Sleep Medicine (AASM) first proposed the application of telemedicine in 2015 to increase access to care for patients with OSAHS, particularly in rural or underserved areas where access to sleep specialists may be limited(29). Patients can undergo a sleep study in the comfort of their own homes using portable monitoring devices. The data from the sleep study can be transmitted to a sleep specialist, who can then diagnose the condition and recommend appropriate treatment options.

In recent years, various sleep-related apps have offered sleep analysis, sleep journals, assessment of insomnia and sleep apnea, and promote individual medical treatment and therapeutic intervention according to the app analysis results(30). Although using a mobile app for OSAHS screening and diagnosis is still in its early stages, initial studies have shown promising results. For example, a study published in the Journal of Sleep Research found that a smartphone app could detect OSAHS accurately in patients, with a sensitivity of 82.9% and a specificity of 94.8%(31). This result is promising for healthcare providers looking for innovative ways to improve the detection and management of OSAHS.

Despite more researchers exploring the possibility of using mobile technology to assist with screening for OSAHS, given that there are over 20 signals detected by PSG, selecting the most accurate and reliable signals for use in mobile technology screening is an ongoing challenge(32). Currently, the most commonly used signals for OSAHS screening through mobile technology include oral-nasal airflow(33), electrocardiogram (ECG)(34), blood oxygen saturation(35), and snore sounds(36). Among these signals, snore sounds are relatively easy to obtain and record without direct contact with the patient. Snoring sounds are generated by the friction between airflow passing against the soft tissues in the upper airway, such as the soft palate, uvula, and tonsils, resulting from a partial sleep obstruction.

Interestingly, snoring is the most apparent sign of apnea, and its acoustic characteristics reflect the changes in upper airway structure(37). The acoustic analysis can identify differences in the snoring sounds between patients with and without OSAS. For example, patients with OSAS may have more intense snoring sounds, longer duration, and more irregular patterns than patients without OSAS. Nearly 75% of snorers suffer from OSAHS, highlighting the importance of snore sounds in screening(38).

The use of snore sounds for detecting OSAHS has been explored in several studies, with promising results(39-40). Dirk Pevernagie et al.

summarized various methods for snoring analysis and modeling(41), including linear predictive coding, wavelet analysis, and hidden Markov model. These methods aim to distinguish snoring events from other sound events and to differentiate between simple snorers and OSA patients. Mesquita et al. found that snoring intervals are related to respiratory disease and that detecting snoring intervals can accurately predict the disease with 91% accuracy(42). Hao et al. extracted various features from snoring signals to identify pathological snore sounds of OSAHS(43). Fiz et al. classified snoring signals based on fundamental frequency and spectral peak(44). These studies suggest that using snoring signals to identify OSAHS patients could be a promising way to develop a home test that is portable, inexpensive, and efficient to screen and diagnose. Furthermore, snore sounds can be recorded without direct contact with the patient, making it a contactless OSAHS detection method.

We are able to find some apps for OSAHS screening and management on the United States apple app store, such as Snore Lab, Firefly, and Sara. However, their accuracy, feasibility, and acceptability by clinicians still need to be determined. A systematic review of 35 studies that evaluated the accuracy of mobile apps for OSAHS screening found that the sensitivity and specificity of the apps varied widely, ranging from 15% to 100% and 20% to 100%, respectively(45). The study concluded that most studies had limitations, such as a small sample size, lack of validation against gold-standard diagnostic tests, and incomplete reporting of diagnostic accuracy measures. These limitations indicate that further research is required to determine the accuracy and feasibility of mobile apps for OSAHS screening and management.

There are also several mobile apps for OSAHS in China. Chinese companies develop some apps, while others are international apps available in China. Some examples of OSAHS apps in China are: 1. Tiantian AI: This app uses AI technology to monitor snoring sounds and provide users with an analysis of their sleep quality. It also offers personalized suggestions for improving sleep and reducing snoring; 2. Sleep Better: This app tracks users' sleep patterns and provides personalized recommendations for improving sleep quality. It also includes features for monitoring snoring and detecting sleep apnea; 3. Snore Circle: This app uses a wearable device that attaches to the user's forehead to monitor snoring and detect sleep apnea. It provides real-time feedback on snoring intensity and frequency and can also track sleep patterns and provide personalized recommendations for improving sleep quality; 4. WIMI Hologram: This app uses holographic technology to simulate a sleep laboratory and provide users with a virtual sleep test. It also includes features for tracking sleep patterns and providing personalized recommendations for improving sleep quality. However, these apps are not widely used by clinicians in China due to accuracy, feasibility, and acceptability of these apps are uncertain(46).

The Dr.Being mobile app is a commercially available app for OSAHS screening. This app has been developed by clinicians and researchers from the Department of Obstructive Sleep Apnea Lab at the Shanghai Sixth Hospital. It uses validated questionnaires and algorithms to collect data on sleep patterns, snoring, and other symptoms. Based on the collected data, the app can provide personalized feedback and recommendations to patients and clinicians. Whether the Dr.Being app has the potential to be used as an OSHAS mobile screener and accepted by clinicians needs further investigation. The present work aims to explore the possibility of a Dr.Being mobile app for OSAHS screening in Chinese adults and evaluate its performance in a clinical study. We will describe the functions and validation of the app, assess its screening accuracy compared to PSG, and evaluate its feasibility and acceptability among Chinese patients and clinicians.

2. Materials and Methods

2.1 System overview and typical use procedure

The Dr. Being app, along with its software development kit (SDK), has been specifically designed to evaluate the severity of OSAHS by determining the Apnea Hypopnea Index (AHI) and screening for OSAHS risk. The app can be conveniently installed on mobile devices like Apple or Android smartphones. The app analyzes snoring patterns and sound frequency and estimates total snoring time. Based on this analysis, it calculates an OSAHS risk score.

The severity of the AHI detecting approach utilizes 1. Snore episode detection (and pauses of time length, indicative of apnea or hypopnea); 2. Snoring sound frequency recognition (Mel-frequency cepstral coefficients (MFCC) and volume information (VI)) to detect snore sounds, changes in sound volume (and acoustic energy around a specific frequency, indicative of apnea or hypopnea)(47).

This study also utilized a comprehensive approach to assessing OSAHS severity, which involved recording overnight audio signals, analyzing sound waveforms, and calculating the Snore-Specific Apnea Hypopnea Index (ssAHI) for each snore episode, which involved determining the number of apnea and hypopnea events occurring in the hour before a snoring episode. Additionally, we extracted Mel-frequency cepstral coefficients (MFCC) and

Vocal Instability (VI) features from each snore episode. By analyzing these features, we were able to obtain a comprehensive understanding of the OSAHS severity for each snoring sound. This multi-faceted approach allowed for a more comprehensive understanding of OSAHS severity and represented a significant step forward in diagnosing and treating this condition.

To use the Dr. Being app, the user needs to download it from the Android or Apple app store and install it on their mobile phone. The app is free and requires no additional equipment or payment. Once installed, the user can start the screening process by pressing the "start screening" button and placing the phone on a bedside table with the microphone pointed towards the head region, about one meter from the person. For the best screening results, it is recommended to keep the phone connected to a power charging cord and conduct the screening for at least 4 hours while the person sleeps. The user can stop the screening process when the person wakes up. Detailed instructions for optimal app use can be found in Figures 1 and 2.

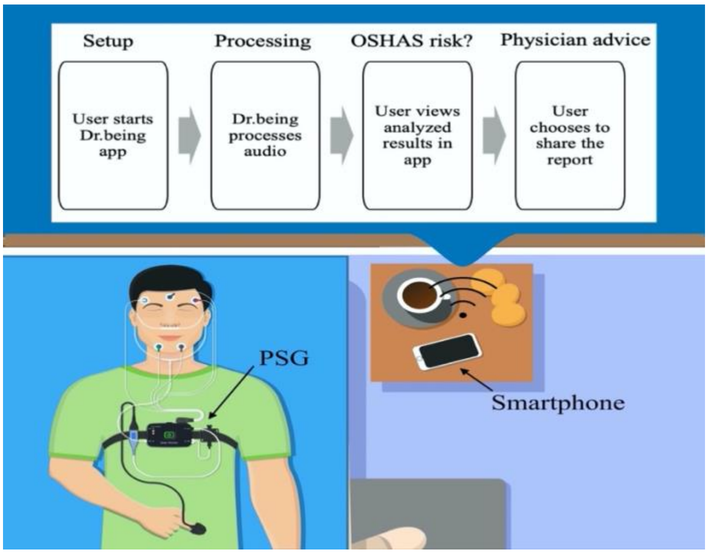


Figure 1: Overview of Polysomnography (PSG) and the Dr.Being OSAHS screening app screening procedure.

Figure 2: Wireframes of Dr.Being app screenshots of OSAHS AHI score and the severity analysis report.

2.2 General data collection

A total of 50 patients with complaints of snoring and apnea at night were selected as study subjects from the Sleep Center of Shanghai Sixth People's Hospital. Basic socio-demographic and health data, such as age, sex, standing height, and body weight, were collected to meet the inclusion criteria. The inclusion criteria for the study included: age above 18 years, a chief complaint of snoring and apnea at night, no previous experience with sleep monitoring or OSAHS treatment, and informed consent. Patients suspected of having central sleep apnea, with irregular shift work in the past three months, and those with chronic obstructive pulmonary disease, pulmonary hypertension, pneumonia, heart failure, myocardial infarction, or neuromuscular disease were excluded from the study.

The OSAHS screening app was investigated with the approval of the Medical Ethics Committee of Shanghai Sixth People's Hospital, with reference number 2022-ky-146(k). Additionally, all study subjects provided informed consent prior to participating in the study.

2.3 OSAHS screening methods

All participants underwent a whole night of sleep measurement at the Sleep Center of Shanghai Sixth People's Hospital, which included simultaneous recordings using a Polysomnography (PSG) and the Dr. Being

OSAHS screening app on their smartphones. In order to mitigate recording bias, patients were instructed to place their phone within 50-150 centimeters of their pillow and ensure that the microphone was directed towards their head, have the phone connected to a power source, and set it to airplane mode for the entire night. Patients were allowed to sleep in any comfortable position during the study.

Specific screening methods:

The Dr. Being app was used for OSAHS screening by instructing patients to register an account with the app on their smartphone, clicking the "Start monitoring" button before sleeping, and collecting snoring and breathing sound data throughout the night. Upon waking up, they clicked "End monitoring," and the Dr. Being app provided the starting and ending time of the screening, the patient's total sleep time, number of snore episodes, total snoring time, a recording of the entire night's snoring sound, and an OSAHS AHI analysis score. This score is a specific screening score given by the Dr. Being app based on AHI analysis.

Different methods were employed to analyze the data collected by Dr.Being and PSG. For polysomnography (PSG): The patients underwent PSG in the sleep center, following the method recommended by the American Academy of Sleep Medicine(48). The recording signals included electroencephalogram (EEG) from several areas of the scalp, bilateral electrooculogram, mandibular electromyogram, thermal signals from the mouth and nose, nasal airflow pressure, respiratory movement of the chest and abdomen, electrocardiogram, snoring, body position, bilateral anterior tibial electromyogram, pulse oxygen saturation, and heart rate(49). The PSG data comprised the start and end times of OSAHS screening, total sleep time, total snoring time, and the snore index (SI). In addition, the study measured several outcomes, including the number of snoring events per hour, the number of snoring events per hour associated with obstructive events, and the apnea-hypopnea index (AHI).

For the results obtained from Dr.Being were automatically interpreted by software, while the PSG data were manually interpreted based on the American Academy of Sleep Medicine (2012) scoring standard. This standard is widely recognized in sleep medicine for assessing sleep disorders.

This analysis defined apnea as the disappearance or decrease of nasal airflow (≥90% below baseline) lasting at least 10 seconds during sleep. The Dr.Being analysis software automatically recorded the total sleep time (TST) and apnea-hypopnea index (AHI). In contrast, TST recorded by PSG was obtained through electroencephalogram analysis, which measures brain waves during sleep.

The severity of sleep apnea was determined by calculating the apnea-hypopnea index (AHI), which represents the number of apneas and hypopneas per hour of sleep. The AHI was calculated using the total sleep time (TST) data obtained from both Dr.Being and PSG. The TST represents the amount of time spent asleep during the recording period. This measure is important for calculating the AHI accurately, as it reflects the denominator in the AHI equation. Therefore, the AHI was calculated by dividing the total number of apneas and hypopneas by the TST in hours. The AHI is widely used to assess the severity of sleep apnea.

AHI threshold interpretation for a result of OSAHS:

- AHI < 5 events / h: Normal (No OSAHS)
- AHI ≥ 5 events / h: Mild OSAHS
- AHI ≥ 15 events / h: Moderate OSAHS
- AHI ≥ 30 events / h: Severe OSAHS

2.4 Statistical methods

The data analysis was conducted using SPSS version 29 software, a widely used statistical analysis tool. The collected monitoring data was found to have a skewed distribution, indicating that it may not follow a normal pattern. A non-parametric approach was used to identify outliers or extreme values that could affect the overall results. For between-group comparisons, the Wilcoxon rank-sum test was utilized. This statistical test is particularly useful when comparing two groups that may not follow a normal distribution, and it assesses the median of the two groups to determine whether there is a significant difference between them.

Typically, the researchers employed linear correlation analysis and Bland-Altman plots to analyze the agreement between the two methods used in the study. Linear correlation analysis was used to determine the strength of the relationship between the variables, while Bland-Altman plots were used to assess the agreement between the two measurement methods(50). The study evaluated the Dr. Being app's ability to detect mild, moderate, and severe cases of OSAHS and reported the results in a cross table (Table 1) and several performance metrics. These metrics included sensitivity, specificity, positive predictive value, negative predictive value, prevalence, and accuracy.

The sensitivity was computed as the true positive rate divided by the sum of true positive and false negative rates. Specificity was calculated as the true negative rate divided by the sum of false positive and true negative rates. The positive predictive value was computed by dividing the true positive rate by the sum of true positive and false positive rates. The negative predictive value was computed by dividing the true negative rate by the sum of false negative and true negative rates. Prevalence was calculated as the proportion of true positive cases in the total study population. Finally, accuracy was calculated as the sum of true positive and true negative rates divided by the total study population.

Table 1: Cross table of sensitivity, specificity, and accuracy between Dr.Being app and Polygraphy.

		Polygraphy (Gold Standard)	
		OSAHS	Non-OSAHS
Dr.Being app	OSAHS	True positive (TP)	False positive (FP)
	Non-OSAHS	False negative (FN)	True negative (TN)

3. Results

3.1 General data collected

There were 60 patients enrolled in the research. However, some patients were excluded from the analysis due to various reasons. Specifically, out of 61 patients, 6 failed to upload their data successfully to the analysis platform, 2 patients failed to record their data, and 3 patients' smartphone screens froze, leading to incomplete original recordings. As a result, 50 patients completed the OSHAS monitoring process, including 36 males (72%) and 14 females (28%).

The participants had a mean age of 48.6 years, with a standard deviation of 16.2 years and a range of 30-69 years. Their mean Body Mass Index (BMI) was 28.8 kg/m^2, with a standard deviation of 4.0 kg/m^2.

3.2 Screening performance of different AHI thresholds for OSHAS between Dr.Being and PSG

This study aimed to compare the accuracy of two methods for diagnosing obstructive sleep apnea-hypopnea syndrome (OSAHS): the Dr.Being method and the polysomnography (PSG) method. The study used three different AHI (apnea-hypopnea index) threshold levels (5, 15, and 30 events/h) to compare the screening results of the two methods in Table 2-4.

The result showed that when the AHI threshold of the Dr.Being app was at

5, 15, and 30 events/h, the accuracy of the OSA prediction was 90%, 76%, and 84%, respectively. The sensitivity of Dr.Being at 5, 15, and 30 events/h was 92.5%, 75.9%, and 57.1%, respectively. Specificity was low when AHI thresholds was at 30 events/h, as shown in Table 5.

3.3 The comparison of the AHI and TST between Dr.Being and PSG

This test aimed to compare the accuracy of the Dr.Being method and polysomnography (PSG) method in measuring AHI (apnea-hypopnea index) and TST (total sleep time) in patients with obstructive sleep apnea-hypopnea syndrome (OSAHS).

The result showed a significant difference ($P<0.05$) in both AHI and TST results between Dr.Being and PSG, as shown in Table 6. However, there was a positive agreement and moderate correlation ($r=0.657$, $P<0.001$; $R2 = 0.438$) between the AHI measured by Dr.Being and PSG, as depicted in Figure 3. In contrast, there was only a low positive correlation agreement ($r=0.181$, $P=0.036$; $R2 = 0.032$) between the TST obtained by Dr.Being and PSG, as shown in Figure 4.

The Bland-Altman plot showed that the mean difference between AHI measured by Dr.Being and PSG was -6.1 (95%CI, -41.3, 28.7) events/h, as illustrated in Figure 5. The error tended to increase as the mean AHI increased, indicating that the accuracy of the screening result measured by Dr.Being decreased as the OSAHS severity increased.

Table 9: compares the diagnostic results of the Dr. Being app and PSG in detecting obstructive sleep apnea-hypopnea syndrome (OSAHS).

	PSG (the gold standard of diagnosis AHI ≥ 5)		TOTAL
Dr.Being	OSAHS	Non-OSAHS	
OSAHS	37	2	39
Non-OSAHS	3	8	11
TOTAL	40	10	50

Note: 1. Normal (No Obstructive Sleep Apnea-hypopnea Syndrome): AHI < 5 events / h

Table 10: The compared diagnostic results of the Dr. Being app and PSG in detecting moderate obstructive sleep apnea-hypopnea syndrome.

	PSG (the gold standard of diagnosis AHI ≥ 15)		TOTAL
Dr.Being	M. OSAHS	NM. OSAHS	
M. OSAHS	22	5	27
NM. OSAHS	7	16	23
TOTAL	29	21	50

Note: 1. Moderate OSAHS: AHI ≥ 15 events / h.

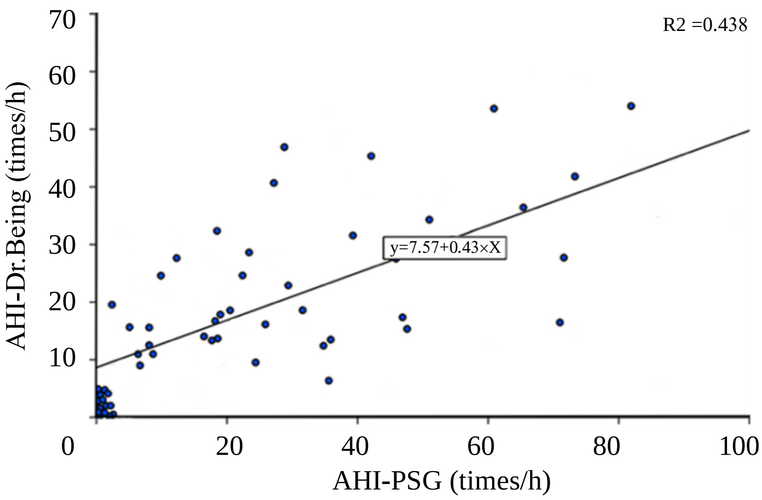
Abbreviations: M. = Moderate, NM. = Non-Moderate.

Table 11: The compared diagnostic results of the Dr. Being app and PSG in detecting severe obstructive sleep apnea-hypopnea syndrome.

	PSG (the gold standard of diagnosis AHI ≥ 30)		
Dr.Being	S. OSAHS	NS. OSAHS	TOTAL
S. OSAHS	8	2	10
NS. OSAHS	6	34	40
TOTAL	14	36	50

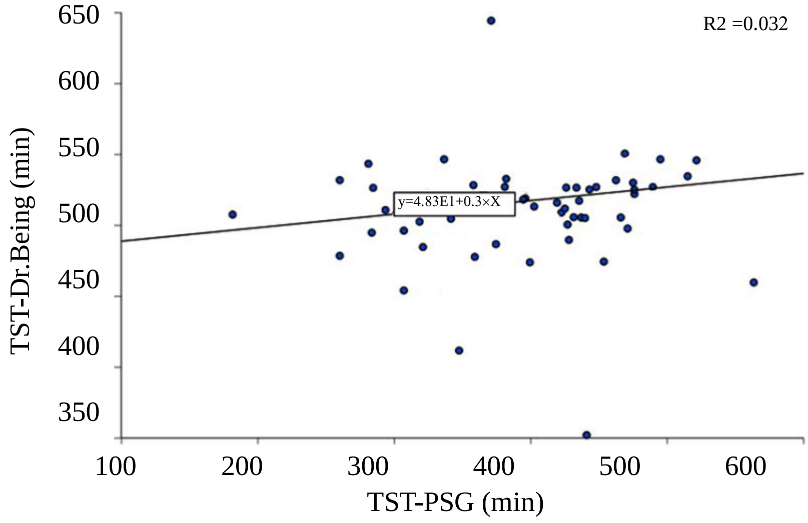
Note: 1. Severe OSAHS: AHI ≥ 30 events / h.

Abbreviations: S. = Severe, NS. = Non-Severe.



Note: PSG = polysomnography, AHI = apnea-hypopnea index

Figure 3: A linear correlation analysis to compare the apnea-hypopnea index (AHI) values obtained by the Dr. Being app and PSG.



Note: TST = total sleep time

Figure 4: A linear correlation analysis to compare the total sleep time (TST) obtained by the Dr. Being app and PSG.

	Diagnostic standard (events/h)		
	AHI ≥ 5	AHI ≥ 15	AHI ≥ 30
Prevalence	80.0	58.0	28.0
Sensitivity (95%*CI*)	92.5	75.9	57.1
	(81.7, 98.1)	(58.5, 88.8)	(31.7,80.2)
Specificity (95%*CI*)	80.0	76.2	94.4
	(50.1, 96.4)	(55.6, 90.7)	(83.8,99.1)

Positive predictive value (%)	94.9	81.5	75.0
Negative predictive value (%)	72.7	69.6	86.7
Accuracy (%)	90.0	76.0	84.0

Table 12: the performance of the Dr. Being app and accuracy across three different AHI threshold levels

Table 13: The compared the diagnostic results of Dr.Being and PSG monitoring indicators [n=50, (P25, P75)].

Screening methods	**AHI (times/h)**	**TST (min)**
Dr.Being app	16.02 (6.27, 26.98)	524.33 (498.49, 547.75)
PSG	17.87 (6.42, 36.23)	407.78 (363.82, 463.24)
Z score	-2.576	-9.497
P value	0.007	<0.001

Note: PSG = polysomnography, AHI = apnea-hypopnea index, TST = total sleep time

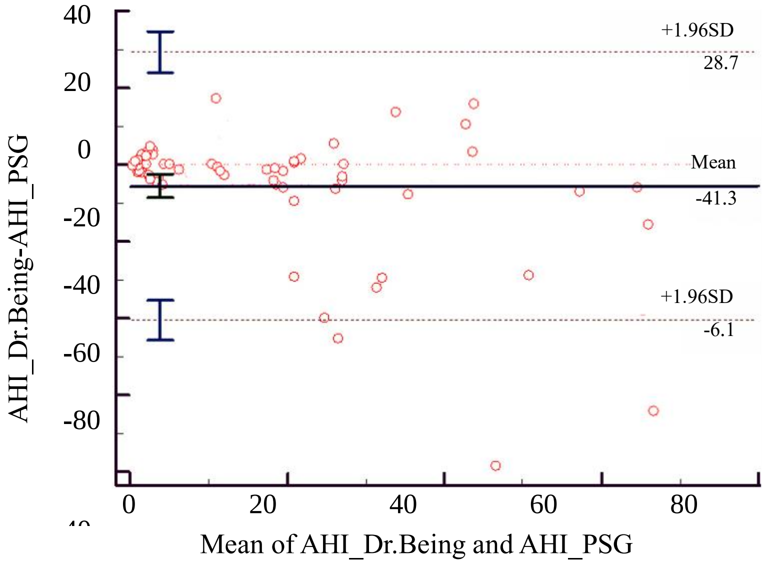


Figure 5: A Bland-Altman consistency analysis evaluated the agreement between AHI values obtained by the Dr. Being app and PSG.

4. Discussion

4.1 Summary of main findings

This study provides validation for the use of a smartphone application for the accurate screening of OSAHS. The collaboration between the key laboratory of Sleep Apnea at a public hospital in Shanghai, China, and the developers of the Dr.Being application has resulted in the first commercially available mobile application for OSAHS screening.

The study found that Dr.Being app had a high diagnostic accuracy of 90% and a sensitivity of 92.5% for screening patients with an AHI ≥ 5, which includes mild, moderate, and severe cases of OSAHS. However, the accuracy of the application in diagnosing the AHI threshold, particularly for patients with moderate-to-severe OSAHS, was lower.

One reason for this lower accuracy is that the TST recorded by Dr.Being was significantly longer than that recorded by PSG, which is considered the gold standard for diagnosing OSAHS. Since Dr.Being is a contactless device and lacks sensors to record physical body signals like EEG, which is used to determine actual sleep time accurately, this discrepancy might have contributed to some degree of inaccuracy when screening for the AHI threshold of OSAHS. Furthermore, the median AHI recorded by Dr.Being was lower than that recorded by PSG, which may have further impacted the screening accuracy.

Despite the limitations mentioned earlier, the study revealed a good agreement between Dr.Being and PSG in detecting OSAHS. Correlation analysis and the Bland-Altman consistency test demonstrated a positive agreement between the two methods, with only 6% of cases having differences outside the limit of agreement. These differences were only observed in patients with a severe form of OSAHS, characterized by an AHI of 30 times/hour or more.

4.2 Comparing diagnostic accuracy of OSAHS screening app in previous research

Snoring, a common symptom of OSAHS, is characterized by airway obstruction, affecting approximately 25% of women and 45% of men in the general population (51). Habitual snoring has been identified as a risk factor for an increased incidence of cardiovascular disease and may indicate the potential development of obstructive sleep apnea (52). Recent studies suggest that the vibration pattern of snoring can identify the onset of pauses during exhalation and inhalation, which are related to the degree of obstruction (53). Furthermore, snoring sound intensity has been significantly associated with respiratory distress index in 39 patients who underwent PSG, even after controlling for demographic and clinical factors (54).

There have been numerous studies investigating snoring as a potential indicator of OSAHS. For example, Zaffaroni et al. (55) conducted a study with

178 volunteers who simultaneously underwent PSG and smartphone software screening throughout the night. The study used a semi-automatic algorithm based on a Gaussian mixture model and found that the clinical threshold of AHI was 15 events/h, with a sensitivity of 94% and specificity of 97%. In this study, the sensitivity and specificity of AHI in diagnosing moderate to severe patients were 75.9% and 76.2%, respectively. Another study by Nakano et al. (56) diagnosed 50 volunteers using PSG, with data from 10 patients used to develop the program and data from 40 patients used to test the program on a smartphone. The researchers analyzed the data in real time using a fast Fourier transform. They found that the sensitivity and specificity of the smartphone in diagnosing OSAHS (AHI ≥ 15 events / h) were 70% and 94%, respectively. However, for subjects with AHI < 30 events / h, the correlation between AHI analyzed by the smartphone and AHI obtained by PSG was not high, so the diagnostic accuracy of this program may not be sufficient to use it as a screening tool for early detection of OSAHS.

In recent years, several studies in China have developed Android-based application software that combines snoring, breathing, and blood oxygen signals using the EEMD-CO algorithm. This innovative signal processing algorithm can analyze non-stationary and non-linear time series data by combining two existing techniques, EEMD and CCA, to detect and process the endpoint of the snoring signal, resulting in high accuracy rates for screening OSAHS patients(57). Dr.Being, the subject of this study, uses the phone's built-in microphone to capture ambient noise, evaluate and calculate snoring frequency, and analyze breathing sounds to obtain AHI. The study found that Dr.Being had high sensitivity (92.5%) and specificity (80.0%) in screening for OSAHS when AHI was ≥ 5 events/hour. However, its sensitivity was low (57.1%), and specificity was high (94.4%) when AHI was ≥ 30 events/hour. This difference in sensitivity and specificity may be due to variations in audio signal processing and algorithms.

Although Dr.Being has shown promising results in screening OSHAS, it is essential to consider the limitations of our study. The validation of Dr.Being was tested in a single hospital room setting, and its accuracy for screening OSHAS in more complex environments, such as with two-bed partners with different background sounds, requires further investigation. Additionally, our study analyzed only a limited number of patients, and more extensive research is needed before Dr.Being can be promoted to the market. It is important to note that smartphones are a useful method to screen underdiagnosed OSHAS patients and can greatly serve in large-scale screening, but they cannot replace PSG. Overall, further research is necessary to validate the effectiveness of Dr.Being and similar smartphone-based tools in diverse populations and settings.

4.3 Limitations of mobile health screening app

While telemedicine offers numerous benefits, it also has downsides(58). These include limited physical exams since healthcare providers cannot physically examine patients, which may hinder accurate diagnoses and identification of potential issues. Technical difficulties may also arise, such as internet connectivity and video/audio quality issues, leading to frustration for patients and healthcare providers. Additionally, telemedicine can feel impersonal, making it harder for healthcare providers to build rapport with patients who prefer in-person visits. Moreover, some patients may lack access to the technology or internet connection necessary for telemedicine appointments, limiting their ability to receive care. Finally, telemedicine is a relatively new field, and there are still legal and regulatory issues, such as privacy and security concerns, that need to be addressed.

Although telemedicine has downsides, the Dr. Being app is a notable exception as it offers a non-invasive, contactless solution for snoring screening. The app has demonstrated superior effectiveness in detecting Obstructive Sleep Apnea Hypopnea Syndrome (OSAHS) in the comfort of patients' homes, surpassing the performance of PSG, which relies on monitoring breathing, blood oxygen levels, and body movements. One of the strengths of the app is its high specificity. Furthermore, it doesn't disrupt the user's sleep patterns, which is an added benefit.

5. Conclusions

Obstructive Sleep Apnea Hypopnea Syndrome (OSAHS) is a widespread sleep disorder affecting individuals globally. Its prevalence rates vary across different regions, with higher rates reported in Asia and lower rates in Africa. The Dr.Being app is valuable in screening Chinese patients with mild OSAHS, aiding in early detection. While the app's functions cannot replace polysomnography (PSG), the gold standard diagnostic tool, it has the potential to screen many patients living in regions with poor medical facilities, serving as a convenient early detection tool. In conjunction with clinicians' evaluation and follow-up treatment, the Dr.Being app can help prevent comorbidities' development and improve the quality of life of affected individuals. As such, the Dr.Being app can be a valuable tool for improving the diagnosis and management of early OSAHS in Chinese adults, especially in regions with limited access to medical facilities.

Conflicts of Interest: There is no conflict of interest in this thesis.

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