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Association between pollinosis and obstructive sleep apnea hypopnea syndrome in the US population: evidence from the NHANES database 2005–2018

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Abstract

Background Rhinobyon and inflammation associated with pollinosis may elevate the risk of obstructive sleep apnea hypopnea syndrome (OSAHS). However, the exact nature of this association remains unclear, particularly in large-scale populations. This study aimed to examine the relationship between pollinosis and OSAHS using data from the National Health and Nutrition Examination Survey (NHANES).

Methods Data from the NHANES spanning 2005 to 2018 were analyzed. Three multivariate generalized linear models (GLMs) were employed to explore the relationship between pollinosis and OSAHS: one unadjusted model, one minimally adjusted model, and one fully adjusted model. Stratified analyses were conducted to assess the impact of pollinosis and other covariates on OSAHS. Additionally, the study incorporated K-Nearest Neighbors (KNN) and smoothed curves to refine the analysis.

Results The study identified significant demographic differences between groups in factors such as pollinosis, age, gender, weight (WT), body mass index (BMI), waist circumference (WC), protein, and fat. In three adjusted models, a consistent association was observed between pollinosis and OSAHS. Specifically, Model 1 showed an odds ratio (OR) of 1.31 [95% confidence interval (CI): 1.16–1.48, $P < 0.001$], Model 2 revealed an OR of 1.35 (95% CI: 1.19–1.54, $P < 0.001$), and Model 3 indicated an OR of 1.29 (95% CI: 1.10–1.50, $P = 0.002$), suggesting that the relationship between pollinosis and OSAHS remained robust despite the inclusion of other covariates. Risk stratification confirmed that pollinosis was a risk factor for OSAHS (OR = 1.28, 95% CI: 1.10–1.50, $P = 0.002$). The KNN model further supported the utility of pollinosis as a diagnostic marker for OSAHS. Smoothing curves also demonstrated a positive correlation between pollinosis prevalence and OSAHS incidence.

Conclusion This study established pollinosis as a risk factor for OSAHS, emphasizing the need for vigilance in monitoring and managing OSAHS in individuals with pollinosis risk.

Keywords Obstructive sleep apnea hypopnea syndrome, Pollinosis, NHANES, Association analysis, Risk stratification analysis

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Introduction

Obstructive sleep apnea hypopnea syndrome (OSAHS) is a prevalent sleep disorder. The adult prevalence of OSAHS is approximately 4%, primarily resulting from upper airway obstruction during sleep, leading to intermittent apneas [1, 2]. OSAHS represents a substantial risk factor for cardiovascular diseases and premature aging. The sleep disturbances associated with OSAHS impair cognitive function, thereby heightening the likelihood of motor vehicle accidents [3–5]. Consequently, OSAHS has become a major global public health issue. Investigating its risk factors is essential for the prevention of its onset and progression, as well as for enhancing treatment strategies [6, 7].

Pollinosis is a hypersensitivity reaction commonly triggered by pollen exposure during the spring and autumn when plants release allergens. In susceptible individuals, inhalation of pollen may lead to symptoms such as nasal congestion, rhinorrhea, pruritus, and conjunctival redness, significantly disrupting daily activities [8–11]. A multinational survey revealed that the incidence of pollinosis in adults was 14.4% [12]. Current management strategies for pollinosis primarily involve allergen avoidance, symptomatic pharmacotherapy, and etiological treatments [8].

The National Health and Nutrition Examination Survey (NHANES), a comprehensive multi-stage sampling survey managed by the Centers for Disease Control and Prevention. This dataset is characterized by standardized data collection procedures, diverse and widespread sampling, high generalizability, and robust representativeness [13, 14]. Numerous studies have utilized the NHANES dataset. Nevertheless, no studies to date have explored the association between pollinosis and OSAHS using the NHANES database.

The present study utilizes adult questionnaire data from the NHANES database (2005–2018) to investigate the association between pollinosis and OSAHS. It seeks to evaluate the potential of pollinosis as an early diagnostic and preventive marker for OSAHS, offering a scientific foundation and novel insights for clinical application.

Materials and methods

Study design and participants

Launched in 1971 by the Centers for Disease Control and Prevention, the NHANES (https://www.cdc.gov/nchs/nhanes) is a comprehensive program designed to evaluate the health and nutritional status of the U.S. population. It employs a complex, stratified, multistage sampling technique, collecting data from approximately 10,000 participants biannually through interviews and physical examinations. Since 1999, the database has been publicly available, providing valuable insights for research and the formulation of health policies. Participation requires informed consent, ensuring that individuals' involvement is fully voluntary and based on adequate understanding [15].

This study included participants from the NHANES survey conducted between 2005 and 2018. The exclusion criteria were as follows: 1. Individuals who either declined to answer or responded "Don't know" regarding the occurrence of pollinosis episodes in the past 12 months, or those with incomplete data for this item. Missing or incomplete data could have introduced bias and disrupted the analysis of relationships between pollinosis and other health variables. 2. Participants without data on OSAHS. Without this data, an effective analytical model could not be constructed, which impacted the exploration of the relationships between OSAHS and other factors. 3. Participants missing information on any of the following covariates: age, gender, race, poverty income ratio (PIR), weight (WT), body mass index (BMI), waist circumference (WC), energy, protein, carbohydrate, sugar, fiber, fat, vitamin E (V_E), vitamin A (V_A), vitamin C (V_C), calcium (Ca), iron (Fe), and zinc (Zn) [16–18]. Missing data on these covariates could have led to confounded results, making it more difficult to establish clear relationships between the main variables of interest. After applying these criteria, 6,516 participants were included in the final analysis (Table 1).

The definition of variables and building baseline profiles

In this study, OSAHS, pollinosis, and relevant covariates were defined using questionnaire responses (Additional file 1). OSAHS diagnosis was determined based on responses to survey questions SLQ030 ("How often do you snore?") and SLQ040 ("How often do you snort/stop breathing?") [15]. Participants who answered "occasionally" or "frequently" to either question were categorized as having OSAHS and placed in the OSAHS group. Those who responded "no" or "rarely" were assigned to the non-OSAHS control group. Additionally, based on question SLQ120 ("How often do you feel overly sleepy during the day?"), respondents who selected "almost always" were included in the OSAHS group, while those who answered "never," "rarely," "sometimes," or "often" were designated as controls. Pollinosis was identified through question AGQ030 ("Episode of hay fever in the past 12 months"), with participants answering "Yes" classified as having pollinosis and placed in the pollinosis group. Those responding "No" were assigned to the control group without pollinosis.

To evaluate the influence of potential covariates on OSAHS, we selected a series of key variables based on previous studies and included potential confounders in the final analysis [19–21]. Specifically, these included:

Table 1 Primary screening of the study population

Variable	Excluding condition	Number
OSAHS	Exclude missing values, refusals, and unknown	24078
Age	Exclude missing values	24078
Gender	Exclude missing values	24078
Race	Exclude missing values	24078
Poverty Income Ratio (PIR)	Exclude missing values	21795
Weight (WT)	Exclude missing values	21480
Body mass index (BMI)	Exclude missing values	21446
Waist circumference (WC)	Exclude missing values	20607
Energy	Exclude missing values	19694
Protein	Exclude missing values	19694
Carbohydrate	Exclude missing values	19694
Sugar	Exclude missing values	19694
Fiber	Exclude missing values	19694
Fat	Exclude missing values	19694
Vitamin E (V_E)	Exclude missing values	19694
Vitamin A (V_A)	Exclude missing values	19694
Vitamin C (V_C)	Exclude missing values	19694
Calcium (Ca)	Exclude missing values	19694
Ferrum (Fe)	Exclude missing values	19694
Zinc (Zn)	Exclude missing values	19694
Pollinosis	**Exclude missing values, refusals, and unknown**	**6516**

age, gender, race, PIR, WT (kg), BMI (kg/m^2), WC (cm), energy (kcal), protein (g), carbohydrate (g), sugar (g), fiber (g), fat (g), V_E (mg), V_A (mg), V_C (mg), Ca (mg), Fe (mg), and Zn (mg). Age was categorized into two groups: 0–79 years and 80 years and older. Gender was classified as male or female. Race was divided into five categories: Mexican American, non-Hispanic white, other Hispanic, non-Hispanic black, and other races. PIR was categorized into two levels: less than 1 and 1 or greater. With the exception of the categorical variables listed, all other covariates were treated as continuous.

Subsequently, baseline characteristics of both the OSAHS and control groups were analyzed using the table one package (v 0.13.2) [22] to identify potential differences between the groups. Weighted chi-square tests assessed differences in baseline characteristics, with statistical significance set at $P<0.05$. Categorical variables were reported as percentages, and a table summarizing the baseline data was generated.

Analysis of association and risk stratification

To further examine the impact of covariates on the relationship between pollinosis and OSAHS, and to assess potential variations in the odds ratio (OR) between the two, two adjusted models were developed under the assumption of interaction between all covariates and OSAHS. Using the survey package (v 4.2) [23], three successive multivariate generalized linear models (GLMs) were constructed to calculate adjusted odds ratios (ORs) with corresponding 95% confidence intervals (CIs). Model 1, unadjusted, assessed the direct association between pollinosis and OSAHS. Model 2, which built on Model 1, provided minimal adjustment, controlling for age, race, and gender. Model 3, the fully adjusted model, incorporated additional adjustments for PIR, WT, BMI, WC, energy, protein, carbohydrate, sugar, fiber, fat, V_E, V_A, V_C, Ca, Fe, and Zn.

To assess the consistency of the association between pollinosis and OSAHS risk across different populations, this study incorporated pollinosis along with various covariates, grouped the study participants, evaluating their interactions with OSAHS using weighted logistic regression. A forest plot was generated using the forest plot package (v 3.1.1) [24], offering a concise visual summary of the results. Subsequently, in order to explore whether the association between allergic rhinitis and OSAHS varied among different patient subgroups, significant categorical variables were selected, and chi-square tests were conducted to analyze whether the association between allergic rhinitis and OSAHS was statistically significant in each subgroup ($P<0.05$).

Development of K-Nearest Neighbors (KNN) model and smoothing curves

Based on exposure factors and other variables, a K-Nearest Neighbors (KNN) model was developed using the caret package (v 6.0–93) [25] to assess the predictive value of various covariates for OSAHS. The model used the "cv" method for tenfold cross-validation, with other parameters set to default values. The accuracy was used as the evaluation metric to select the optimal model, with the parameters that maximized the accuracy chosen. Next, a random forest (RF) model was constructed using the randomForest package (v4.7–1.1) based on the same exposure factors and other variables [26]. The random seed was set to set.seed(8500), and the number of decision trees was set to 500. The optimal tree was determined by minimizing the error rate to rank the importance of the variables. Finally, an Xgboost model was built using the xgboost package (v1.7.3.1) [27] with predefined parameters (max_depth = 3, eta = 1, nthread = 2, nrounds = 10, objective = "binary:logistic"), and a SHAP model was established with the shapviz package (v0.9.6) [28]. The variables were ranked based on their contributions in the SHAP model, and a SHAP dependence plot was then created to display the SHAP value distribution for pollinosis. The importance of each variable was determined by its contribution to the KNN model. To

further examine the association between pollinosis and OSAHS, a smooth curve was generated based on Model 3 using ggplot2 (v 3.4.4) [29], visualizing the relationship between pollinosis and OSAHS incidence.

Statistical analysis

Statistical analyses were performed using the nhanesR package in R (v 4.2.2), with a significance threshold set at $P<0.05$. The software used in this article is shown in Additional file 2.

Results

Demographic differences between OSAHS patients and controls

After excluding certain samples and defining the variables, 6,516 participants were included in the analysis, comprising 3,258 individuals in the control group and 3,258 in the OSAHS group. The baseline characteristics table (Table 2) outlined the differences in variables between the two groups. Among these, 677 participants had both pollinosis and OSAHS, 538 had pollinosis without OSAHS, 2,581 had OSAHS without pollinosis, and 2,720 had neither condition, revealing a significant association between pollinosis and OSAHS ($P<0.001$). Furthermore, significant demographic disparities were noted between the OSAHS and control groups regarding age, gender, WT, BMI, WC, protein, and fat, indicating that these covariates also contributed notably to OSAHS ($P<0.001$).

Identified pollinosis as a contributing exposure factor for OSAHS

Subsequent association analysis was performed using three models: an unadjusted model and two adjusted models (minimally and fully adjusted). The results revealed a consistent and statistically significant relationship with OSAHS across all models ($P<0.05$). In Model 1, the odds ratio (OR) was 1.31 (95% CI: 1.16–1.48,

Table 2 The baseline characteristics table of the participants

	level	No	Yes	*p*
n		3258	3258	
Pollinosis (%)	No	2720 (83.5)	2581 (79.2)	< 0.001
	Yes	538 (16.5)	677 (20.8)	
Race (%)	Mexican American	508 (15.6)	534 (16.4)	0.122
	Non-Hispanic Black	734 (22.5)	704 (21.6)	
	Non-Hispanic White	1556 (47.8)	1504 (46.2)	
	Other Hispanic	300 (9.2)	358 (11.0)	
	Other Race	160 (4.9)	158 (4.8)	
Age (%)	≥ 80	234 (7.2)	153 (4.7)	< 0.001
	0–79	3024 (92.8)	3105 (95.3)	
Gender (%)	Female	1852 (56.8)	1567 (48.1)	< 0.001
	Male	1406 (43.2)	1691 (51.9)	
PIR (%)	0–1	719 (22.1)	680 (20.9)	0.252
	≥ 1	2539 (77.9)	2578 (79.1)	
WT (mean (SD))		75.62 (18.73)	86.72 (22.31)	< 0.001
BMI (mean (SD))		27.08 (6.06)	30.76 (7.37)	< 0.001
WC (mean (SD))		93.59 (15.70)	103.30 (16.77)	< 0.001
Energy (mean (SD))		2054.08 (1011.11)	2140.10 (1069.44)	0.001
Protein (mean (SD))		77.43 (42.30)	81.26 (44.47)	< 0.001
Carbohydrate (mean (SD))		252.27 (130.14)	257.21 (135.16)	0.133
Sugar (mean (SD))		116.02 (80.46)	117.77 (84.03)	0.391
Fiber (mean (SD))		15.42 (9.78)	15.41 (9.92)	0.959
Fat (mean (SD))		77.67 (47.50)	82.31 (49.30)	< 0.001
V_E (mean (SD))		7.16 (5.53)	7.30 (5.79)	0.301
V_A (mean (SD))		607.65 (758.85)	567.20 (520.68)	0.012
V_C (mean (SD))		88.34 (96.97)	82.87 (98.01)	0.024
Ca (mean (SD))		902.14 (599.60)	890.43 (568.50)	0.419
Fe (mean (SD))		14.60 (8.84)	14.72 (8.50)	0.569
Zn (mean (SD))		11.06 (6.98)	11.83 (11.59)	0.001

P < 0.001), in Model 2, it was 1.35 (95% CI: 1.19–1.54, *P* < 0.001), and in Model 3, it was 1.29 (95% CI: 1.10–1.50, P = 0.002) (Table 3). These findings suggest that the association between pollinosis and OSAHS remained stable despite adjustments for covariates, emphasizing the potential significance of monitoring and managing OSAHS in individuals with or at risk for pollinosis.

Evaluating pollinosis as a potential risk factor for OSAHS

A further risk stratification analysis, incorporating pollinosis and other covariates, was performed and visualized using a forest plot (Fig. 1). The analysis confirmed that pollinosis was significantly associated with OSAHS, serving as an independent risk factor (OR = 1.28, 95% CI: 1.10–1.50, P = 0.002), indicating that individuals with pollinosis face an elevated risk of developing OSAHS. In addition, strong associations were observed between OSAHS and several other factors, including age (0–79), gender (male), BMI, and WC, all of which were found to increase the likelihood of OSAHS (OR > 1, *P* < 0.05). The chi-square test results showed that a significant association between allergic rhinitis and OSAHS was found in the 0–79 age group, as well as in the male and female subgroups (Table 4).

Table 3 Risk association analysis between pollinosis and OSAHS

	SII	Odds radio	95% Confidence interval	*p*_ value
PollinosisYes	model 1	1.31	1.31(1.16–1.48)	< 0.001
	model 2	1.35	1.35(1.19–1.54)	< 0.001
	model 3	1.29	1.29(1.1–1.5)	0.002

Increased OSAHS risk in patients with pollinosis

The KNN model demonstrated that pollinosis served as a reliable diagnostic marker for OSAHS (Fig. 2 a and Additional file 3). The RF model further demonstrated that pollinosis had predictive value for OSAH(Fig. 2b). The subsequent SHAP model revealed that pollinosis positively influenced the model's predictions, increasing the probability or value of the prediction with a contribution range between -0.25 and 0.75 (Fig. 2c-d). A smoothing curve was then generated to illustrate the relationship between pollinosis and OSAHS prevalence (Fig. 3). The curve revealed a positive correlation, suggesting that pollinosis occurrence was strongly associated with OSAHS

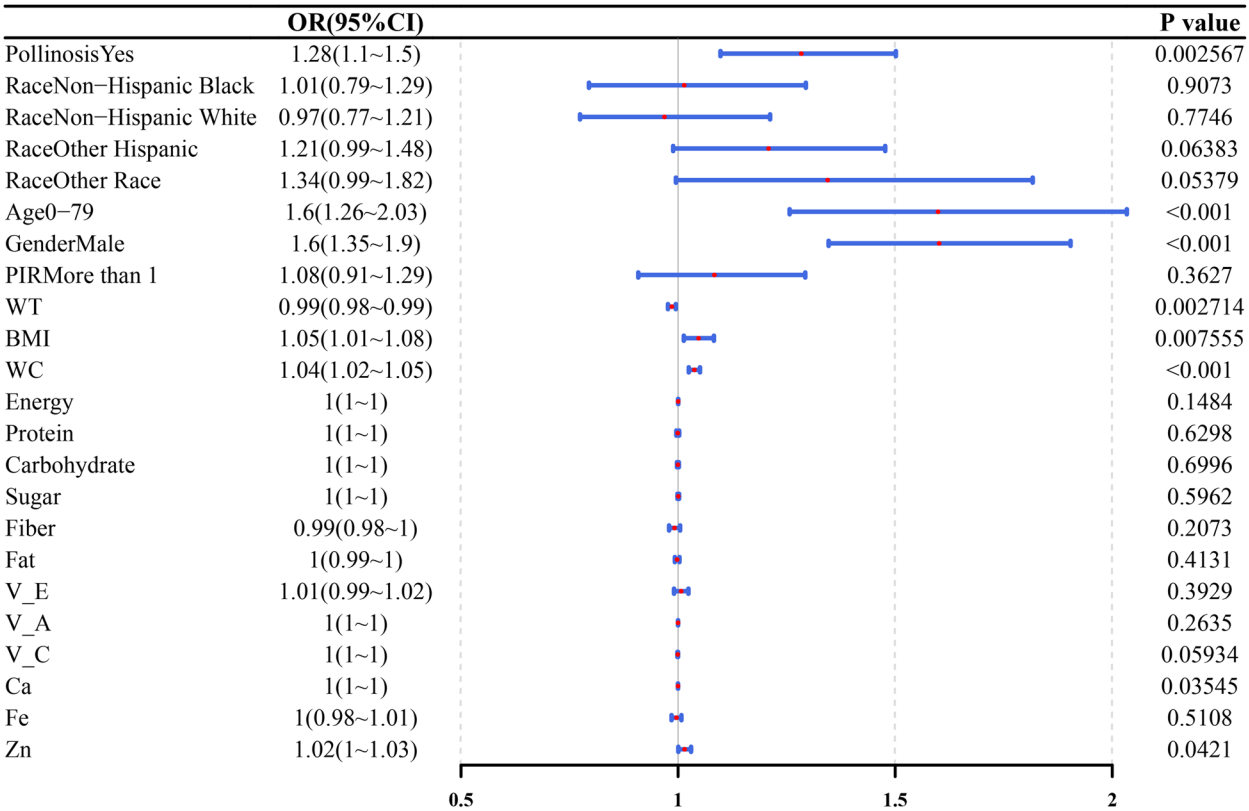

Fig. 1 Stratified analysis of OSAHS patients

Table 4 Table of chi square test results for age and gender subgroups

		level	No	Yes	*p*
0–79 years	*n*		3024	3105	
	Pollinosis (%)	No	2513 (83.1)	2451 (78.9)	< 0.001
		Yes	511 (16.9)	654 (21.1)	
> 80 years	*n*		234	153	
	Pollinosis (%)	No	207 (88.5)	130 (85.0)	0.397
		Yes	27 (11.5)	23 (15.0)	
Male	*n*		1406	1691	
	Pollinosis (%)	No	1213 (86.3)	1372 (81.1)	< 0.001
		Yes	193 (13.7)	319 (18.9)	
Female	*n*		1852	1567	
	Pollinosis (%)	No	1507 (81.4)	1209 (77.2)	0.003
		Yes	345 (18.6)	358 (22.8)	

incidence, and patients with pollinosis typically had a higher probability of developing OSAHS.

Discussion

This study, utilizing the NHANES database, is the first to report the prevalence of OSAHS among individuals with pollinosis, confirming a significant association between pollinosis and OSAHS risk. In all three models developed, pollinosis consistently emerges as a risk factor for OSAHS, demonstrating its predictive value. These results offer a robust foundation for the prevention and early diagnosis of OSAHS.

OSAHS has emerged as a significant global public health issue, affecting 936 million individuals worldwide to varying degrees [30]. Recent studies increasingly highlight allergic rhinitis (AR) as a risk factor for OSAHS [31–33]. The prevalence of moderate- and high-risk OSAHS is notably higher in individuals with AR compared to the general population [34]. Research indicates that AR can lead to upper airway stenosis, thereby increasing the risk of OSAHS, with treatment of AR shown to alleviate OSAHS severity [35]. Additionally, a correlation between sleep disorders and allergic diseases has been established, with OSAHS patients being 2.72 times more likely to develop pollinosis than the general population [36]. Consequently, further investigation into the relationship between pollinosis and OSAHS may help prevent or mitigate the onset and progression of OSAHS.

A review of the baseline characteristics revealed significant differences in established risk factors for OSAHS—such as age, gender, WT, BMI, and WC—between the control and OSAHS cohorts, consistent with previous studies [37–39]. Additionally, pollinosis, high protein intake, and increased fat consumption were found to influence OSAHS risk, with individuals diagnosed with pollinosis showing a notably higher incidence of OSAHS compared to the control group. These results highlight the role of pollinosis and other covariates in the development of OSAHS. By identifying these associations, high-risk populations can be more effectively recognized, providing a foundation for targeted prevention strategies and early intervention. Furthermore, the P values for pollinosis across all three models were less than 0.05, indicating that the impact of pollinosis on OSAHS remained independent of other covariates, reinforcing the need to monitor OSAHS risk in patients with pollinosis.

Based on existing research, we have summarized some possible mechanisms and disease progression processes. The association between pollinosis and OSAHS risk may involve both inflammatory and anatomical pathways. Specifically, pollinosis driven allergic inflammation can exacerbate upper airway obstruction through mucosal swelling and inflammatory mediator release [40]. IgE-mediated hypersensitivity triggers eosinophilic infiltration and the release of proinflammatory cytokines (such as IL-4, IL-5, TNF-α), leading to mucosal edema and nasal congestion.IgE [41]. Such inflammatory responses may spread to the pharynx, reducing airway lumen diameter and increasing airway collapsibility during sleep. Second, chronic nasal congestion can induce compensatory oral-breathing, which may alter the oropharyngeal anatomy over time [42]. Future studies should quantify real-time changes in the airways during pollen exposure using longitudinal imaging methods and verify the above hypothesis through mechanistic experiments.

Risk stratification analysis and the KNN machine learning algorithm identified pollinosis, age (0–79), gender (male), BMI, and WC as significant risk factors for OSAHS. Men typically have larger tongues and soft palates, with increased fat deposition in the oropharynx, leading to a higher incidence of OSAHS. Likewise,

(See figure on next page.)

Fig. 2 The study explored the predictive value of variables for OSAHS using machine learning. **a** The importance ranking of variables in KNN model. **b** The importance ranking of variables in RF model. On the left was the selection of random decision trees, with the ordinate representing the error rate, and the optimal tree corresponded to the lowest error rate; in the right figure, the abscissa was the importance value and the ordinate was the variable. **c** The bar chart of variable importance in the SHAP model. The abscissa was the shap value and the ordinate was the mean value of variables. **d** The variable dependence graph of pollinosis. The abscissa was pollinosis (1 and 2) and the ordinate was the distribution of shap values

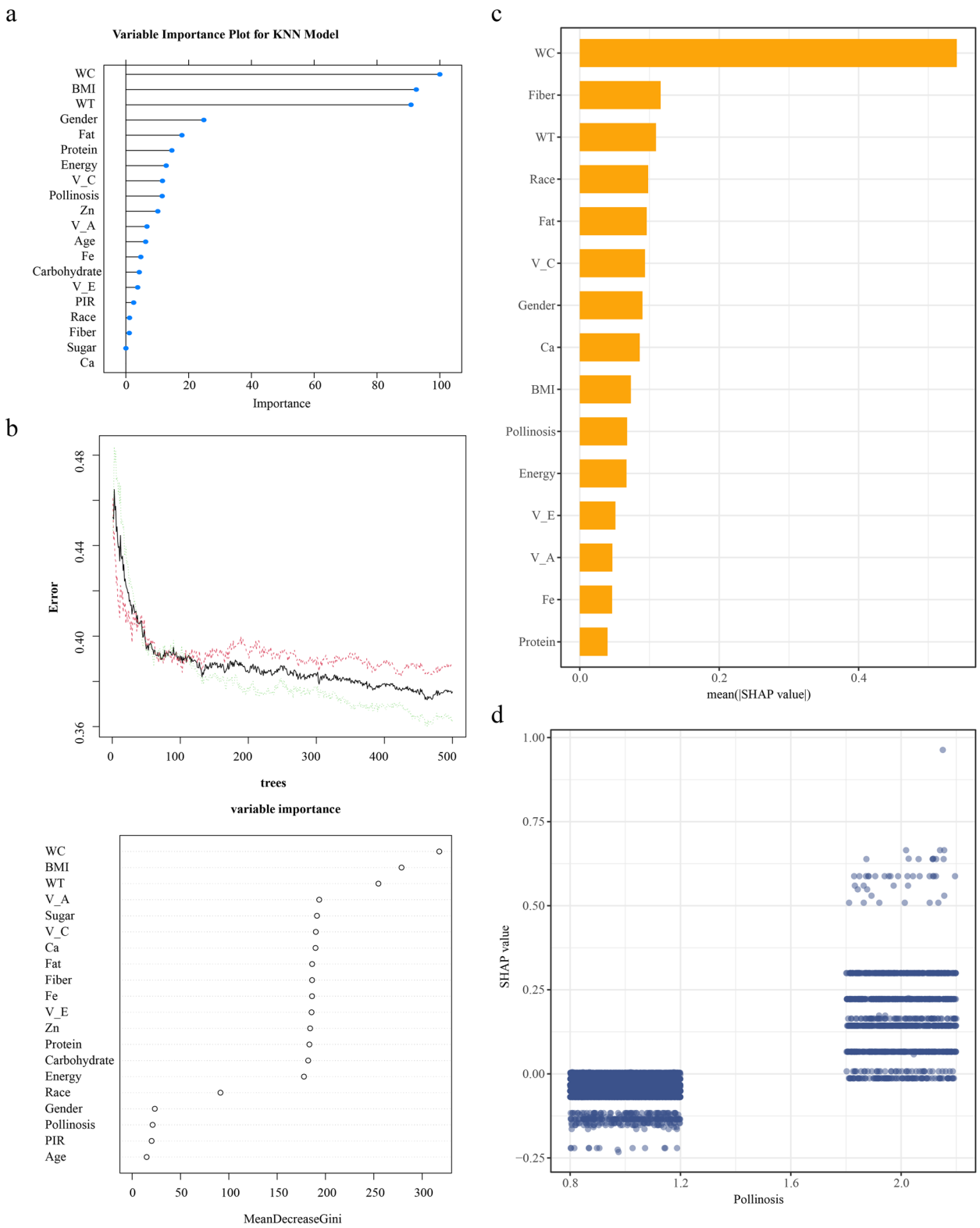

Fig. 2 (See legend on previous page.)

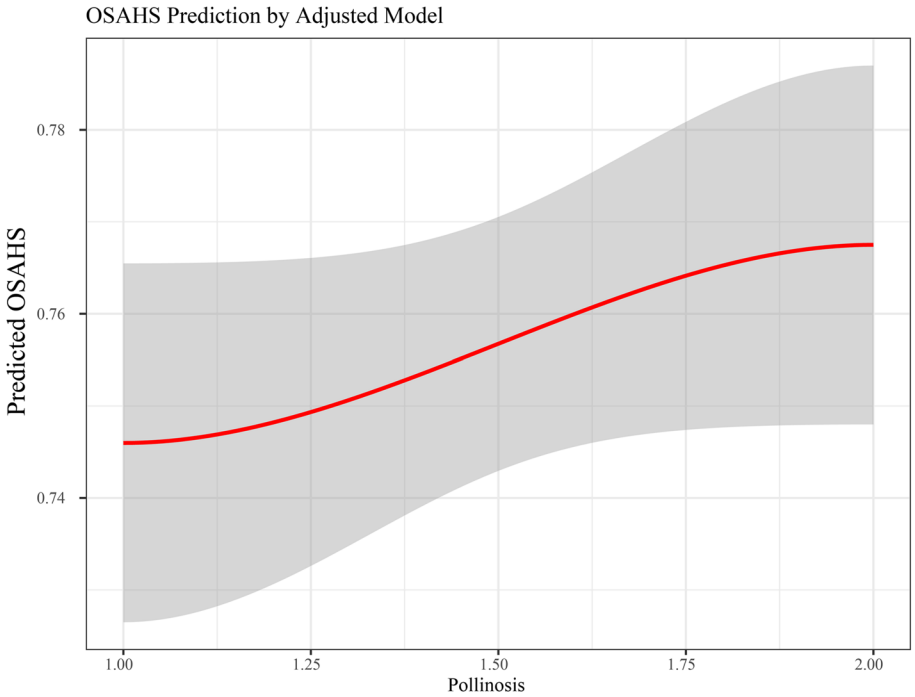

Fig. 3 Relationship between pollinosis and OSAHS prevalence based on Model 3. The x-axis represented the pollen allergy status, with 1 indicating pollen allergy patients and 2 indicating non-pollen allergy patients

obesity, characterized by elevated BMI and WC, contributes to local fat accumulation in the oropharynx, further elevating OSAHS risk [43]. These results highlight the need for comprehensive prevention strategies that account for various risk factors, particularly when developing tailored interventions for specific demographics. Effective identification and management of high-risk populations can substantially reduce OSAHS incidence. The positive correlation observed in the smooth curve suggests that pollinosis significantly increases the likelihood of OSAHS development. This insight emphasizes the potential of pollinosis as a key health indicator in predicting OSAHS, offering substantial value for clinical diagnosis and risk assessment.

This study combines the K-Nearest Neighbors (KNN) algorithm, the Random Forest (RF) model, and the SHAP algorithm to deeply explore the relationship between pollinosis and the risk of OSAHS. The KNN algorithm is an instance-based learning method that can effectively handle nonlinear relationships and does not rely on the data distribution pattern, making it particularly suitable for the NHANES dataset with heterogeneous data characteristics [44]. KNN predicts by calculating the distance between the sample to be predicted and the training samples, and then selecting the nearest K neighbors. It has been widely applied in multiple NHANES data studies [45, 46]. At the same time, the Random Forest model, by constructing multiple decision trees and synthesizing the prediction results, can identify the complex interaction relationships between features and has strong noise resistance [47]. When dealing with complex data, RF shows high accuracy and robustness, especially demonstrating its advantages when handling NHANES data [48, 49]. To further improve the interpretability of the model, this study introduces the SHAP algorithm, which provides an in-depth understanding of the decision-making process behind the prediction results and helps to reveal the decision-making mechanism of the model [50]. By integrating the KNN, RF, and SHAP algorithms, this study not only significantly improves the prediction accuracy but also enhances the interpretation of the model's decision-making process, providing a powerful tool for in-depth exploration of the potential relationship between pollinosis and OSAHS.

This research has significant clinical and public health implications. Pollinosis is significantly associated with OSAHS. In clinical practice, physicians need to pay particular attention to patients with a history of pollinosis, especially when these patients exhibit symptoms of sleep apnea. The study findings may help clinicians identify high-risk populations for OSAHS at an earlier stage, particularly those with pollinosis. This identification can prompt early screening and intervention to reduce the risk of complications in patients. The treatment approach

for OSAHS can be adjusted based on the severity of pollinosis.

This study offers several key strengths. First, the NHANES data, which are reliable and widely representative, provide a solid foundation for the analysis. Second, the relationship between pollinosis and OSAHS is thoroughly explored. Baseline data reveal significant differences in pollinosis and other variables—such as age, gender, BMI, and WC—between the disease and control groups, emphasizing the relevance of these covariates in OSAHS risk. Association analysis demonstrates a significant effect of pollinosis on OSAHS within the regulatory model, suggesting it as an independent risk factor. Risk stratification analysis and the KNN machine learning algorithm further corroborate the substantial influence of pollinosis and other factors on OSAHS, while smooth curve analysis confirms the positive correlation between pollinosis and OSAHS. These results provide valuable insights for the management and prevention of OSAHS.

However, this study still has some limitations. First, this study is based on NHANES data and adopts a cross-sectional observational design. Due to its nature, it cannot infer the causal relationship or temporal sequence between pollinosis and the development of OSAHS. Future studies could use longitudinal or prospective designs to better explore the causal relationship between pollinosis and OSAHS. Second, NHANES data use self-reported snoring, daytime sleepiness, and a history of allergic rhinitis as diagnostic criteria, which may have certain limitations. There is a lack of clinical or polysomnography (PSG) validation, and no detailed allergen testing was conducted to confirm the etiology of pollinosis. Therefore, future studies should incorporate more rigorous and objective diagnostic criteria to further validate these results. In addition, although this study controlled for potential confounding factors as much as possible, there may still be uncontrolled factors that could affect the results, such as environmental exposures (air quality, pollen concentration), use of allergy medications, and the severity of pollinosis. These factors may influence the risk of OSAHS and were not fully explored in the analysis. Future studies should consider including these factors in the analysis and using more complex statistical models to address their potential impacts. The NHANES data are mainly derived from the US population, and the study results may not be fully applicable to other countries or regions, especially those with different genetic backgrounds, environmental conditions, or healthcare systems. Therefore, in the future, we plan to validate our findings using independent cohorts or datasets and consider including samples from other countries or regions to improve the generalizability and universality of the results. Finally, due to the limited sample size, future studies should increase the sample size and further validate the correlations we found through experimental studies.

Conclusion

We employed multiple statistical methods to analyze the effects of covariates and pollinosis on OSAHS, ultimately identifying a significant association between the two. Clinically, physicians should screen patients with a history of pollinosis and implement early interventions to reduce their risk of OSAHS-related complications.

Abbreviations

OSAHS	Obstructive sleep apnea hypopnea syndrome
OSA	Obstructive sleep apnea
NHANES	National Health and Nutrition Examination Survey
GLMs	Generalized linear models
KNN	K-Nearest Neighbors
WT	Weight
BMI	Body mass index
WC	Waist circumference
OR	Odds ratio
CI	Confidence interval
VAI	Visceral adiposity index
LAP	Lipid accumulation product
PIR	Poverty income ratio
V_E	Vitamin E
V_A	Vitamin A
V_C	Vitamin C
Ca	Calcium
Fe	Ferrum
Zn	Zinc
SDB	Sleep-disordered breathing
AR	Allergic rhinitis

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12890-025-03581-5.

Additional file 1: Table S1: The definition of OSAHS, pollinosis, and covariates.

Additional file 2: Table S2: R package.

Additional file 3: Specific parameter settings and calculations for KNN models

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Authors' contributions

SZ: Proposed the study, conception and design of the work, have drafted the work and substantively revised it, acquisition and analysis data; JP and TG: Drafted the work and revised it. XL and LJ: Interpretation of data; RL, ZG and HH: Conception of the work and prepared Figs. 1–3. All authors has read and approved the final manuscript.

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Not applicable.

Data availability

The datasets analysed during the current study are available in the [NHANES] repository, [https://www.cdc.gov/nchs/nhanes/index.htm].

Declarations

Ethics approval and consent to participate
The date of NHANES has been approved by the the National Center for Health Statistics Research Ethics Evaluation Committee.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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