



Apr 29, 2025

🌐 AI-driven bone mineral density prediction from chest x-rays and its association with obstructive sleep apnea

📖 [PLOS One](#)

DOI

<https://dx.doi.org/10.17504/protocols.io.x54v9wbopl3e/v1>

Hung-Lung Tsai¹

¹Tungs' Taichung MetroHarbor Hospital



KuanHung Cheng

Tungs' Taichung Metroharbor Hospital

Create & collaborate more with a free account

Edit and publish protocols, collaborate in communities, share insights through comments, and track progress with run records.

Create free account

OPEN  ACCESS



DOI: <https://dx.doi.org/10.17504/protocols.io.x54v9wbopl3e/v1>

External link: <https://doi.org/10.1371/journal.pone.0330080>

Protocol Citation: Hung-Lung Tsai 2025. AI-driven bone mineral density prediction from chest x-rays and its association with obstructive sleep apnea. **protocols.io** <https://dx.doi.org/10.17504/protocols.io.x54v9wbopl3e/v1>



Manuscript citation:

Tsai H, Cheng K, Lin P, Hsu Y, Chen S (2025) AI-driven bone mineral density prediction from chest x-rays and its association with obstructive sleep apnea. PLOS One 20(9). doi: [10.1371/journal.pone.0330080](https://doi.org/10.1371/journal.pone.0330080)

License: This is an open access protocol distributed under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited

Protocol status: Working

We use this protocol and it's working

Created: April 28, 2025

Last Modified: April 29, 2025

Protocol Integer ID: 189870

Keywords: Sleep Apnea, Obstructive; Osteoporosis; Machine Learning, bone health metric, driven bone mineral density prediction, relationship between these bone health metric, bone mineral density, osteoporosis screening, cxr imaging for osteoporosis screening, osteoporosis, association with obstructive sleep apnea, potential relationship between obstructive sleep apnea, obstructive sleep apnea, lumbar spine bmd, overall skeletal health, gold standard for bmd assessment, bmd assessment, assessment of osa risk, body mass index, cxr examinations at tung, free screening tool with promising clinical application, using cxr imaging, cxr examination

Funders Acknowledgements:

Tungs' Taichung MetroHarbor Hospital

Abstract

With an increasing aging population, the prevalence of chronic comorbidities is on the rise. The potential relationship between obstructive sleep apnea (OSA) and osteoporosis has garnered significant attention. Most studies examining the association between these two conditions have relied on dual-energy X-ray absorptiometry (DXA) to evaluate bone mineral density (BMD). Although DXA is considered the gold standard for BMD assessment, it does not reflect overall skeletal health.

The limitations of conventional measurements are particularly pronounced in patients with multisystemic diseases, such as OSA. To address these limitations, we applied VeriOsteoTMOP software to predict lumbar spine BMD and T-scores from chest X-ray (CXR) images. In addition, we examined the relationship between these bone health metrics and OSA. A total of 70,395 patients who underwent CXR examinations at Tungs' Taichung MetroHarbor Hospital from 2017 to 2022 were included. Eligible samples were selected based on the presence of an OSA ICD-10-CM diagnosis code along with DXA results.

By incorporating variables, such as gender, age, Body Mass Index (BMI), and T-score, we used multiple machine learning models, including logistic regression, random forest, and XGBoost, to analyze the risk for OSA. The results indicated that when the BMI range was controlled, the predictive contribution of the T-score became significant. For some models, the area under the curve (AUC) reached over 85% in both the training and validation datasets. This suggests a notable association between T-score and OSA, which is maintained when confounding variables such as BMI are controlled.

This study highlights the potential of artificial intelligence (AI) technology using CXR imaging for osteoporosis screening. Combining CXR with machine learning models enables the assessment of OSA risk and offers a cost-effective, radiation-free screening tool with promising clinical applications.

Materials

Data resources

This was a cross-sectional, retrospective study that included patients who underwent CXR examination at Tungs' Metro Harbor Hospital from January 2017 to December 2022. Initially, 70,395 CXR-PA images were collected, and the image dataset was subsequently transformed into a tabular dataset. The tabular data consisted of X-ray PA view images taken from 2017 to 2022, which were analyzed using VeriOsteoTMOP software to obtain BMD and T-scores. The data were sourced from the electronic medical record system of Tungs' Metro Harbor Hospital and spanned a six-year data collection period to ensure that the data was diverse and representative. The data used in this study were accessed on February 1, 2024, from the database of Tungs' Metro Harbor Hospital. This study was conducted in accordance with the principles of the Declaration of Helsinki and followed current scientific guidelines. As the data were fully anonymized to protect patient confidentiality, the requirement for informed consent was waived.

Inclusion and exclusion criteria

To ensure data quality and the reliability of the results, multiple exclusion criteria were established. First, patients had to meet at least one of the following conditions: (1) having a diagnosis of OSA confirmed by the ICD-10-CM code G47.33, or (2) having undergone a DXA scan. The diagnosis code G47.33 was assigned based on clinical judgment by physicians, and patients did not undergo polysomnography (PSG). Patients meeting either condition were included in the dataset (n = 5,480), whereas patients with missing BMI data were excluded (n = 607). Further exclusions included those with abnormal BMI values below 18.5 or above 60 (n = 147) and those under 50 years or over 85 years of age (n = 269). The final dataset consisted of 4,457 patients, which was used for preliminary and subgroup analyses (Fig 1).

Step 1: Introduction

- 1
 - Taiwan is projected to become a super-aged society by 2025, with increasing elderly-related diseases like obstructive sleep apnea (OSA) and osteoporosis.
 - OSA and osteoporosis are often comorbid and need integrated clinical attention.
 - OSA-related intermittent hypoxia may promote bone loss.
 - AI is being applied to predict BMD and T-scores from chest X-rays.

Step 2: Materials

- 2 **Data resources**
 - This is a cross-sectional, retrospective study using data from Tungs' Metro Harbor Hospital (2017–2022).
 - CXR images were analyzed using VeriOsteoTMOP to obtain BMD and T-scores.
 - Data were de-identified; informed consent was waived.
- 3 **Ethical Approval**
 - Approved by the IRB of Tungs' Taichung MetroHarbor Hospital (IRB No. 112069).
 - Written informed consent was obtained from all participants.
- 4 **Inclusion/Exclusion Criteria**
 - Inclusion: OSA diagnosis (ICD-10-CM G47.33) or DXA data.
 - Exclusion: Missing BMI, extreme BMI (<18.5 or >60), age <50 or >85.
 - Final sample: 4,457 patients.
- 5 **BMD & T-score Detection**
 - VeriOsteoTMOP (Acer Medical Inc.) version 1.00.3000 used.
 - AI analyzed thoracolumbar (T12–L1) regions from CXR.
 - Performance validated against DXA measurements.

Step 3: Methods

- 6 **Independent variable and outcome variable**
 - Variables: Gender, age, BMI, BMD, T-score.
 - T-score categories per IOF:
 - Normal: T-score > -1.0
 - Low Bone Mass: $-2.5 < \text{T-score} \leq -1.0$
 - Osteoporosis: T-score ≤ -2.5
- 7 **Statistical Analysis**
 - Qualitative data: Chi-square test for gender, T-score groups.
 - Quantitative data: t-test for age, BMI, BMD, T-score.
 - Significance set at $\alpha = 0.05$.
 - Software: Python 3.10.12 with SciPy 1.13.1.



8 **Machine Learning**

- Data split 9:1 (training:validation), 10-fold cross-validation.
- Models: Logistic Regression, Random Forest, XGBoost.
- Evaluated using ROC curve and AUC.

Supplementary material:

- 9 The complete source code, data processing scripts, and additional resources supporting this study are available at Zenodo via the following DOI:
<https://doi.org/10.5281/zenodo.15300281>.

Protocol references

1. Li S, Zan Y, Li F, Dai W, Yang L, Yang R, et al. An analysis of the potential association between obstructive sleep apnea and osteoporosis from the perspective of transcriptomics and NHANES. *BMC Public Health*. 2024 Jul 26;24(1):1998.
2. Chakhtoura M, Nasrallah M, Chami H. Obstructive Sleep Apnea and Osteoporosis Risk. *J Clin Sleep Med JCSM Off Publ Am Acad Sleep Med*. 2015 Sep 15;11(9):1071–2.
3. Melton LJ, Atkinson EJ, O'Connor MK, O'Fallon WM, Riggs BL. Bone density and fracture risk in men. *J Bone Miner Res Off J Am Soc Bone Miner Res*. 1998 Dec;13(12):1915–23.
4. Ko CH, Yu SF, Su FM, Chen JF, Chen YC, Su YJ, et al. High prevalence and correlates of osteoporosis in men aged 50 years and over: A nationwide osteoporosis survey in Taiwan. *Int J Rheum Dis*. 2018 Dec;21(12):2112–8.
5. Samadi B, Samadi S, Samadi M, Samadi S, Samadi M, Mohammadi M. Systematic Review of Detecting Sleep Apnea Using Artificial Intelligence: An Insight to Convolutional Neural Network Method. *Arch Neurosci [Internet]*. 2024 [cited 2025 Mar 10];11(1). Available from: <https://brieflands.com/articles/ans-144058#abstract>
6. Hans D, Baim S. Quantitative Ultrasound (QUS) in the Management of Osteoporosis and Assessment of Fracture Risk. *J Clin Densitom Off J Int Soc Clin Densitom*. 2017;20(3):322–33.
7. Qiao Y, Guo J, Luo J, Huang R, Wang X, Su L, et al. Early bone loss in patients with obstructive sleep apnea: a cross-sectional study. *BMC Pulm Med*. 2024 Jan 11;24(1):28.
8. Xu X, Zhou X, Liu W, Ma Q, Deng X, Fang R. Evaluation of the correlation between frailty and sleep quality among elderly patients with osteoporosis: a cross-sectional study. *BMC Geriatr*. 2022 Jul 19;22(1):599.
9. Yen TY, Ho CS, Chen YP, Pei YC. Diagnostic Accuracy of Deep Learning for the Prediction of Osteoporosis Using Plain X-rays: A Systematic Review and Meta-Analysis. *Diagn Basel Switz*. 2024 Jan 18;14(2):207.
10. Franklin KA, Lindberg E. Obstructive sleep apnea is a common disorder in the population—a review on the epidemiology of sleep apnea. *J Thorac Dis*. 2015 Aug;7(8):1311–22.
11. Daltro CH da C, Fontes FH de O, Santos-Jesus R, Gregorio PB, Araújo LMB. [Obstructive sleep apnea and hypopnea syndrome (OSAHS): association with obesity, gender and age]. *Arq Bras Endocrinol Metabol*. 2006 Feb;50(1):74–81.
12. Lee W, Nagubadi S, Kryger MH, Mokhlesi B. Epidemiology of Obstructive Sleep Apnea: a Population-based Perspective. *Expert Rev Respir Med*. 2008 Jun 1;2(3):349–64.
13. Yook S, Kim D, Gupte C, Joo EY, Kim H. Deep learning of sleep apnea-hypopnea events for accurate classification of obstructive sleep apnea and determination of clinical severity. *Sleep Med*. 2024 Feb;114:211–9.
14. Senaratna CV, Perret JL, Lodge CJ, Lowe AJ, Campbell BE, Matheson MC, et al. Prevalence of obstructive sleep apnea in the general population: A systematic review. *Sleep Med Rev*. 2017 Aug;34:70–81.
15. Mitra AK, Bhuiyan AR, Jones EA. Association and Risk Factors for Obstructive Sleep Apnea and Cardiovascular Diseases: A Systematic Review. *Dis Basel Switz*. 2021 Dec 2;9(4):88.
16. Álvarez D, Cerezo-Hernández A, Crespo A, Gutiérrez-Tobal GC, Vaquerizo-Villar F, Barroso-García V, et al. A machine learning-based test for adult sleep apnoea screening at home using oximetry and airflow. *Sci Rep*. 2020 Mar 24;10(1):5332.
17. Millman RP, Redline S, Carlisle CC, Assaf AR, Levinson PD. Daytime hypertension in obstructive sleep apnea. Prevalence and contributing risk factors. *Chest*. 1991 Apr;99(4):861–6.
18. Sies NS, Zaini AA, de Bruyne JA, Jalaludin MY, Nathan AM, Han NY, et al. Obstructive sleep apnoea syndrome (OSAS) as a risk factor for secondary osteoporosis in children. *Sci Rep*. 2021 Feb 4;11(1):3193.

19. Ye P, Qin H, Zhan X, Wang Z, Liu C, Song B, et al. Diagnosis of obstructive sleep apnea in children based on the XGBoost algorithm using nocturnal heart rate and blood oxygen feature. *Am J Otolaryngol.* 2023;44(2):103714.
20. Ankitha V, Manimegalai P, Jose PSH, Raji P. Literature Review on Sleep APNEA Analysis by Machine Learning Algorithms Using ECG Signals. *J Phys Conf Ser.* 2021 Jun;1937(1):012054.
21. Upala S, Sanguankeo A, Congrete S. Association Between Obstructive Sleep Apnea and Osteoporosis: A Systematic Review and Meta-Analysis. *Int J Endocrinol Metab.* 2016 Jul;14(3):e36317.
22. Mirrakhimov AE, Sooronbaev T, Mirrakhimov EM. Prevalence of obstructive sleep apnea in Asian adults: a systematic review of the literature. *BMC Pulm Med.* 2013 Feb 23;13:10.
23. Singh M, Liao P, Kobah S, Wijeyesundera DN, Shapiro C, Chung F. Proportion of surgical patients with undiagnosed obstructive sleep apnoea. *Br J Anaesth.* 2013 Apr;110(4):629–36.
24. Knauert M, Naik S, Gillespie MB, Kryger M. Clinical consequences and economic costs of untreated obstructive sleep apnea syndrome. *World J Otorhinolaryngol - Head Neck Surg.* 2015 Sep;1(1):17–27.
25. Gaines J, Vgontzas AN, Fernandez-Mendoza J, Bixler EO. Obstructive sleep apnea and the metabolic syndrome: The road to clinically-meaningful phenotyping, improved prognosis, and personalized treatment. *Sleep Med Rev.* 2018 Dec;42:211–9.
26. Dewan NA, Nieto FJ, Somers VK. Intermittent hypoxemia and OSA: implications for comorbidities. *Chest.* 2015 Jan;147(1):266–74.
27. Liguori C, Mercuri NB, Izzi F, Romigi A, Cordella A, Piccirilli E, et al. Obstructive sleep apnoea as a risk factor for osteopenia and osteoporosis in the male population. *Eur Respir J.* 2016 Mar;47(3):987–90.
28. Swanson CM, Shea SA, Stone KL, Cauley JA, Rosen CJ, Redline S, et al. Obstructive sleep apnea and metabolic bone disease: insights into the relationship between bone and sleep. *J Bone Miner Res Off J Am Soc Bone Miner Res.* 2015 Feb;30(2):199–211.
29. Haseltine KN, Chukir T, Smith PJ, Jacob JT, Bilezikian JP, Farooki A. Bone Mineral Density: Clinical Relevance and Quantitative Assessment. *J Nucl Med Off Publ Soc Nucl Med.* 2021 Apr;62(4):446–54.
30. Chakhtoura M, Nasrallah M, Chami H. Bone loss in obesity and obstructive sleep apnea: a review of literature. *J Clin Sleep Med JCSM Off Publ Am Acad Sleep Med.* 2015 Apr 15;11(5):575–80.
31. Johnston CB, Dagar M. Osteoporosis in Older Adults. *Med Clin North Am.* 2020 Sep;104(5):873–84.
32. Zhao H, Jia H, Jiang Y, Suo C, Liu Z, Chen X, et al. Associations of sleep behaviors and genetic risk with risk of incident osteoporosis: A prospective cohort study of 293,164 participants. *Bone.* 2024 Sep;186:117168.
33. Tasali E, Ip MSM. Obstructive sleep apnea and metabolic syndrome: alterations in glucose metabolism and inflammation. *Proc Am Thorac Soc.* 2008 Feb 15;5(2):207–17.
34. Arredondo E, Udeani G, Panahi L, Taweeseed PT, Surani S. Obstructive Sleep Apnea in Adults: What Primary Care Physicians Need to Know. *Cureus.* 2021 Sep;13(9):e17843.
35. Chen YL, Weng SF, Shen YC, Chou CW, Yang CY, Wang JJ, et al. Obstructive sleep apnea and risk of osteoporosis: a population-based cohort study in Taiwan. *J Clin Endocrinol Metab.* 2014 Jul;99(7):2441–7.
36. Upala S, Sanguankeo A, Congrete S. Obstructive Sleep Apnea is Not Associated with an Increased Risk of Osteoporosis: a Systematic Review and Meta-Analysis. *J Clin Sleep Med JCSM Off Publ Am Acad Sleep Med.* 2015 Sep 15;11(9):1069–70.
37. Zhao JM, Wang BY, Huang JF, Xie HS, Chen ML, Chen GP. Assessment of bone mineral density and bone metabolism in young men with obstructive sleep apnea: a cross-sectional study. *BMC Musculoskelet Disord.* 2022 Jul 16;23(1):682.

38. Dimai HP. Use of dual-energy X-ray absorptiometry (DXA) for diagnosis and fracture risk assessment; WHO-criteria, T- and Z-score, and reference databases. Bone. 2017 Nov;104:39–43.
39. El Maghraoui A, Roux C. DXA scanning in clinical practice. QJM Mon J Assoc Physicians. 2008 Aug;101(8):605–17.
40. Jain RK, Vokes T. Dual-energy X-ray Absorptiometry. J Clin Densitom Off J Int Soc Clin Densitom. 2017;20(3):291–303.
41. Hsieh CI, Zheng K, Lin C, Mei L, Lu L, Li W, et al. Automated bone mineral density prediction and fracture risk assessment using plain radiographs via deep learning. Nat Commun. 2021 Sep 16;12(1):5472.
42. Tsuiki S, Nagaoka T, Fukuda T, Sakamoto Y, Almeida FR, Nakayama H, et al. Machine learning for image-based detection of patients with obstructive sleep apnea: an exploratory study. Sleep Breath Schlaf Atm. 2021 Dec;25(4):2297–305.
43. Sato Y, Yamamoto N, Inagaki N, Iesaki Y, Asamoto T, Suzuki T, et al. Deep Learning for Bone Mineral Density and T-Score Prediction from Chest X-rays: A Multicenter Study. Biomedicines. 2022 Sep 19;10(9):2323.
44. Tseng SC, Lien CE, Lee CH, Tu KC, Lin CH, Hsiao AY, et al. Clinical Validation of a Deep Learning-Based Software for Lumbar Bone Mineral Density and T-Score Prediction from Chest X-ray Images. Diagn Basel Switz. 2024 Jun 7;14(12):1208.
45. Jang M, Kim M, Bae SJ, Lee SH, Koh JM, Kim N. Opportunistic Osteoporosis Screening Using Chest Radiographs With Deep Learning: Development and External Validation With a Cohort Dataset. J Bone Miner Res Off J Am Soc Bone Miner Res. 2022 Feb;37(2):369–77.
46. Wang C, Zhang Z, Zheng Z, Chen X, Zhang Y, Li C, et al. Relationship between obstructive sleep apnea-hypopnea syndrome and osteoporosis adults: A systematic review and meta-analysis. Front Endocrinol. 2022;13:1013771.
47. Diagnosis | International Osteoporosis Foundation [Internet]. [cited 2025 Apr 23]. Available from: <https://www.osteoporosis.foundation/patients/diagnosis>
48. Li Z, Li Y, Zhao G, Zhang X, Xu W, Han D. A model for obstructive sleep apnea detection using a multi-layer feed-forward neural network based on electrocardiogram, pulse oxygen saturation, and body mass index. Sleep Breath Schlaf Atm. 2021 Dec;25(4):2065–72.
49. Zhu J, Zhou A, Gong Q, Zhou Y, Huang J, Chen Z. Detection of Sleep Apnea from Electrocardiogram and Pulse Oximetry Signals Using Random Forest. Appl Sci. 2022 Apr 22;12(9):4218.
50. Application of various machine learning techniques to predict obstructive sleep apnea syndrome severity - PubMed [Internet]. [cited 2025 Apr 23]. Available from: <https://pubmed.ncbi.nlm.nih.gov/37076549/>
51. Ferreira-Santos D, Amorim P, Silva Martins T, Monteiro-Soares M, Pereira Rodrigues P. Enabling Early Obstructive Sleep Apnea Diagnosis With Machine Learning: Systematic Review. J Med Internet Res. 2022 Sep 30;24(9):e39452.
52. Aiyer I, Shaik L, Sheta A, Surani S. Review of Application of Machine Learning as a Screening Tool for Diagnosis of Obstructive Sleep Apnea. Med Kaunas Lith. 2022 Nov 1;58(11):1574.
53. Keshavarz Z, Rezaee R, Nasiri M, Pournik O. Obstructive Sleep Apnea: A Prediction Model Using Supervised Machine Learning Method. Stud Health Technol Inform. 2020 Jun 26;272:387–90.
54. Leong ZH, Loh SRH, Leow LC, Ong TH, Toh ST. A machine learning approach for the diagnosis of obstructive sleep apnoea using oximetry, demographic and anthropometric data. Singapore Med J. 2025 Apr 1;66(4):195–201.
55. Braley TJ, Dunietz GL, Chervin RD, Lisabeth LD, Skolarus LE, Burke JF. Recognition and Diagnosis of Obstructive Sleep Apnea in Older Americans. J Am Geriatr Soc. 2018 Jul;66(7):1296–302.

56. 國民健康署. 肥胖是慢性疾病！調整飲食及運動生活是最佳處方 [Internet]. 國民健康署. 國民健康署; 2018 [cited 2025 Apr 23]. Available from: <https://www.mohw.gov.tw/cp-3796-42429-1.html>