ORIGINAL ARTICLE

EXTENDED BREASTFEEDING AND POSTMENOPAUSAL OSTEOPOROSIS: A RETROSPECTIVE REAPPRAISAL THROUGH ARTIFICIAL INTELLIGENCE

Uzun Süreli Emzirme ve Postmenopozal Osteoporoz: Yapay Zeka Merceğinden Retrospektif Yeniden Değerlendirme

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ABSTRACT

Objective: This study re-examines clinical and demographic data on osteoporosis in postmenopausal women, with a specific focus on extended breastfeeding (>12 months) as a potential modifiable risk factor. We also explore how artificial intelligence (AI)-based modeling contributes to enhanced risk prediction.

Material and Methods: A retrospective analysis was conducted on 127 osteoporotic and 53 non-osteoporotic postmenopausal women evaluated between 2010 and 2012. Collected variables included age, body mass index (BMI), age at menopause, breastfeeding history, serum osteocalcin levels, dynamic balance scores, and vertebral fracture presence. A Random Forest model was developed and trained using Python with the scikit-learn library. Data were preprocessed (normalization, imputation), and the dataset was split into training and test sets. Multivariate logistic regression was also performed to determine independent predictors.

Results: Osteoporotic women were older (p<0.001), had lower BMI (p<0.001), reached menopause earlier (p=0.035), and more frequently breastfed ≥12 months (p=0.005). Vertebral fractures were observed in 22.8% of osteoporotic patients. Osteocalcin levels and balance errors were sig-nificantly elevated. While breastfeeding was associated with osteoporosis in univariate analysis, multivariate regression revealed that age, BMI, osteocalcin level, and fracture history were stronger independent predictors. The Random Forest model demonstrated potential to detect complex risk patterns across variables.

Conclusion: Extended breastfeeding contributes to osteoporosis risk but is not an independent predictor. AI modeling on original data provided deeper insights and individualized risk estimation, representing a valuable advancement in osteoporosis research.

Keywords: *Artificial Intelligence; Body Mass Index, Breastfeeding, Machine Learning; Menopause; Osteoporosis*

ÖZET

Amaç: Bu çalışma, postmenopozal kadınlarda osteoporozla ilişkili klinik ve demografik verileri yeniden değerlendirmekte; özellikle 12 aydan uzun süren emzirmenin potansiyel olarak değiştirilebilir bir risk faktörü olup olmadığını incelemektedir. Ayrıca, yapay zekâ (YZ) tabanlı modellemenin risk öngörüsüne katkısını ortaya koymayı amaçlamaktadır.

Gereç ve Yöntemler: 2010–2012 yılları arasında değerlendirilen 127 osteoporotik ve 53 osteoporotik olmayan postmenopozal kadının verileri retrospektif analiz edildi. Yaş, beden kitle indeksi (BKİ), menopoz yaşı, emzirme süresi, serum osteokalsin düzeyleri, dinamik denge skorları ve vertebra kırığı varlığı incelendi. Python ve scikit-learn kütüphanesi kullanılarak Random Forest algoritmasıyla gerçek veri seti üzerinde bir YZ modeli oluşturuldu ve eğitildi. Veriler normalize edildi, eksik veriler işlendi ve eğitim/test ayrımı yapıldı. Bağımsız risk faktörlerini belirlemek amacıyla çok değişkenli lojistik regresyon analizi de uygulandı.

Bulgular: Osteoporotik kadınlar daha yaşlıydı (p<0,001), daha düşük BKİ'ye sahipti (p<0,001), daha erken menopoza girmişti (p=0,035) ve ≥12 ay emzirmiş olma oranları daha yüksekti (p=0,005). Osteoporotik grupta vertebra kırığı prevalansı %22,8 idi. Osteokalsin düzeyleri ve denge hataları anlamlı olarak yüksekti. Emzirme süresi tek değişkenli analizde anlamlıydı; ancak çok değişkenli analizde yaş, BKİ, osteokalsin düzeyi ve kırık öyküsü daha güçlü bağımsız belirleyiciler olarak saptandı. YZ modeli, değişkenler arası karmaşık ilişkileri ortaya koyma potansiyeli gösterdi.

Sonuç: Uzun süreli emzirme osteoporoz riskini artırsa da, bağımsız bir belirleyici değildir. Gerçek verilerle oluşturulan YZ modellemesi, bireyselleştirilmiş risk öngörüsü sağlayarak osteoporoz araştırmalarında önemli katkılar sunabilir.

Anahtar Kelimeler: *Yapay Zeka; Beden Kitle İndeksi; Emzirme; Yapay Öğrenme; Menopoz; Osteoporozis*

INTRODUCTION

Osteoporosis is a chronic metabolic bone disease marked by a decrease in bone mineral density (BMD) and deterioration of bone tissue microarchitecture, leading to an increased risk of fractures (1). Globally, it affects more than 200 million individuals, and its prevalence continues to rise in aging populations, especially among postmenopausal women (2). In this demographic, estrogen deficiency accelerates bone resorption, tipping the balance between bone formation and resorption in favor of the latter. Established risk factors for osteoporosis include advanced age, female sex, low body mass index (BMI), sedentary lifestyle, calcium and vitamin D deficiency, smoking, alcohol use, and early menopause (3).

However, among reproductive and gynecologic variables, one potentially underestimated factor is the duration of breastfeeding. While breastfeeding is widely encouraged for its numerous neonatal benefits, it also imposes a temporary but physiologically significant demand on maternal calcium stores. During lactation, up to 400 mg of calcium per day is diverted from maternal bone to breast milk, primarily under the influence of prolactin and parathyroid hormone-related protein (4,5).

Several studies have reported that BMD typically recovers within 6–12 months post-weaning (4-6). However, the degree and timeline of recovery can vary based on individual nutrition, parity, cumulative breastfeeding duration, and hormonal milieu. In populations with high parity and poor nutritional support, extended breastfeeding might lead to long-term reductions in peak bone mass especially when not followed by adequate calcium replenishment or exercise stimulation (7).

Türkiye represents a unique context for studying the intersection of reproductive health and bone health due to its high breastfeeding prevalence, relatively early menopause age, and regional disparities in access to preventive care. Our original 2014 study focused on demo-graphic and gynecological risk factors in postmenopausal women with and without osteoporosis (8). Among other findings, it revealed a statistically significant association between prolonged breast-feeding duration and lower BMD.

In the present paper, we revisit that study with a contemporary lens-reevaluating the original data to highlight breastfeeding as a potentially modifiable osteoporosis risk factor. Additionally, we introduce a conceptual inquiry: what would our study have looked like if artificial intelligence (AI) tools (specifically a Random Forest model) had been available at the time? AI offers capabilities such as natural language processing (NLP), machine learning-based risk stratification, image analysis, and real-time decision supportall of which can substantially enhance the scope, speed, and insight of clinical research (9). This dual-layered exploration aims to reaffirm the clinical relevance of extended breastfeeding as a risk factor while envisioning how future osteoporosis research can evolve through the integration of AI.

MATERIALS AND METHODS

This retrospective observational study analyzed data collected from women aged 50 and older who were evaluated at previous Ankara Bilkent City Hospital Hospital (This hospital currently serves under the roof of Ankara Physical Therapy and Rehabilitation Education and Research Hospital) between May 2010 and June 2012. At the time, ethics committee approval was formally obtained from the Education Planning Committee in accordance with national guidelines. All data were anonymized, and no additional patient intervention or data collection was conducted for the current manuscript. The study complies with the ethical standards of the institutional and national research committees and with the 1964 Helsinki declaration and its later amendments. Patients were grouped into two categories based on their BMD results obtained from dual-energy X-ray absorptiometry (DEXA): an osteoporotic group (T-score ≤ -2.5) and a control group (T-score ≥ -1.0).

Exclusion criteria included secondary causes of osteoporosis, such as endocrine disorders, long-term corticosteroid use, malignancies, or renal insufficiency. Data on age, BMI, age at menopause, breastfeeding duration, parity, physical activity, dietary calcium intake, back pain, vertebral fractures, thoracic kyphosis, paravertebral muscle spasm, dynamic balance test results, and serum osteocalcin levels were extracted from hospital records. The primary objective was to assess whether extended breastfeeding duration

was significantly associated with osteoporosis after menopause.

Statistical analyses were conducted using SPSS v15.0. (IBM SPSS Statistics for Windows, Version 15.0. Armonk, NY: IBM Corp.) Differences between groups were evaluated using Student's t-test, Chi-square test, or Mann–Whitney U test. A significance level of $p < 0.05$ was used. Logistic regression analysis (both univariate and multivariate) was used to determine whether extended breastfeeding was an independent risk factor for osteoporosis. Additionally, we explore an AI-assisted analysis framework including machine learning-based risk stratification, NLP for data extraction, and predictive modeling. In order to achieve this analysis, we used the original study's published statistics and the dataset of the thesis which inspired this study (8).

To evaluate the potential of machine learning in osteoporosis risk prediction, we imple-mented a Random Forest classifier using Python (version 3.9) and the scikit-learn library (version 1.3).

Patients with missing or implausible values in key predictors (e.g., BMI < 15 or > 50 kg/m²) were excluded. Remaining missing values (in <5% of records) were imputed using mean imputation for continuous variables and mode imputation for categorical variables.

Continuous features such as age, BMI, osteocalcin, and balance error scores were normalized using z-score standardization to facilitate equal weighting in tree splits.

Binary variables (e.g., breastfeeding ≥12 months: yes/no, vertebral fracture: present/absent) were encoded as 0 and 1.

The dataset was randomly split into training (80%) and testing (20%) subsets. Stratification ensured proportional representation of osteoporotic and non-osteoporotic cases.

Performance metrics included accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). No external validation was performed due to limited sam-ple size.

The following clinically relevant features were selected based on their known or hypothesized relevance to osteoporosis risk: Age (years), Body Mass Index (BMI, kg/m²), age at meno-pause (years), duration of breastfeeding (≥12 months: yes/no), serum osteocalcin level (ng/mL), dynamic balance errors (number of postural errors during balance test), presence of vertebral fracture (yes/no). These features were chosen for their availability in the original dataset and their established or biologically plausible link to bone mineral density (BMD) and fracture risk.

RESULTS

The osteoporotic group (n=127) had a significantly higher mean age (65.7 ± 8.1 years) compared to the control group (59.4 ± 7.5 years; $p<0.001$), and lower BMI (23.1 ± 3.4 kg/m² vs. 26.2 ± 3.6 kg/m²; $p<0.001$). Earlier age at menopause was observed in the osteoporotic group (mean 45.2 years) compared to controls (mean 47.8 years; $p=0.035$). The prevalence of breast-feeding for ≥12 months was significantly higher among osteoporotic women (62.2%) versus con-trols (37.7%; $p=0.005$). Baseline characteristics of the study groups were presented in Table-1.

Vertebral fractures were found in 22.8% of osteoporotic patients but none in the control group. Symptoms such as back pain, thoracic kyphosis, and paravertebral muscle spasms were significantly more common in the osteoporotic group. Furthermore, dynamic balance tests revealed more errors in this group ($p=0.010$), suggesting greater functional impairment. Osteocalcin levels, indicative of increased bone turnover, were also significantly elevated in the osteoporotic group ($p<0.001$). Comparison of clinical findings and laboratory markers was presented in Table-2.

These results support a strong correlation between extended breastfeeding and postmenopausal osteoporosis, especially when compounded by other risk factors such as low BMI and early menopause.

In addition to traditional statistical analysis, we applied a modern AI-based classification approach using a Random Forest algorithm. The model achieved an impressive AUC of 0.89, indicating strong predictive performance. Among the input features, serum osteocalcin levels (26.4% importance), BMI (17.7%), balance test errors (14.3%), age (13.2%), and menopause age (11.9%) were the top predictors. Breastfeeding for ≥12 months also contributed to the model's predictions with 5.1% relative importance. The model attained a classification accuracy of 87%,

with precision and recall values of 88% and 95%, respectively, for osteoporotic cases. Performance metrics of the AI model for osteoporosis prediction and feature importance ranking based on Random Forest classifier were presented in Table-3 and Table-4. Univariate analysis showed that women who breastfed for ≥12 months had a significantly higher prevalence of osteoporosis ($p<0.05$). However, the results of multivariate logistic regression analysis indicated that age, BMI, osteocalcin, and fractures were independent predictors, while breastfeeding lost significance when adjusted for these factors ($p=0.12$). The relevant results of regression analysis were presented in Table-5. These findings support the relevance of extended breastfeeding in osteoporosis risk but highlight the stronger predictive influence of metabolic and neuromuscular factors. A visual representation of feature importance is provided in Figure 1.

DISCUSSION

This study re-evaluated data collected in the early 2010s to investigate whether extended breastfeeding

Table 1. Baseline characteristics of the study groups.

Variable	Osteoporotic (n=127)	Control (n=53)	p-value	Interpretation
Age (years)	65.7 ± 8.1	59.4 ± 7.5	<0.001	Older in osteoporosis group
BMI (kg/m²)	23.1 ± 3.4	26.2 ± 3.6	<0.001	Lower BMI in osteoporosis group
Menopause age	45.2 ± 3.1	47.8 ± 3.6	0.005	Earlier menopause in osteoporosis group
Breastfeeding ≥12 months	62.2%	37.7%	0.005	More common in osteoporosis group
Fracture prevalence	22.8%	0%	<0.001	Exclusive to osteoporosis group

BMI: body mass index, kg/m²: kilogram/square meter

Table 2. Comparison of clinical findings and laboratory markers.

Variable	Osteoporotic (%)	Control (%)	p-value	Interpretation
Back pain	57.5%	26.4%	<0.001	Significantly higher
Kyphosis	31.5%	11.3%	0.005	More frequent
Paravertebral spasm	51.2%	17%	<0.001	Significantly higher
Osteocalcin (ng/mL)	19.7 ± 4.9	15.7 ± 5.1	<0.001	Higher in osteoporosis
Balance test errors	5.2 ± 2.1	4.2 ± 1.7	0.022	More errors in osteoporosis group

ng/mL: nanogram/milliliter

Table 3. Performance metrics of the AI model for osteoporosis prediction.

Metric	Value
Accuracy	87%
Precision (Osteoporotic)	88%
Recall (Osteoporotic)	95%
F1 Score (Osteoporotic)	91%
AUC	0.89

AUC: area under curve

Table 4. Feature importance ranking based on Random Forest classifier.

Feature	Relative Importance (%)
Osteocalcin	26.4
BMI	17.7
Balance Errors	14.3
Age	13.2
Menopause Age	11.9
Breastfeeding ≥12 months	5.1

BMI: body mass index

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Table 5. Multivariate Logistic Regression Analysis of Osteoporosis Risk Factors

Variable	β Coefficient	Standard Error	Odds Ratio (OR)	95% CI for OR	p-value
Age (years)	0.08	0.02	1.08	1.04–1.12	<0.001
BMI (kg/m²)	-0.12	0.04	0.89	0.83–0.94	<0.01
Menopause Age (years)	-0.03	0.05	0.97	0.88–1.06	0.31
Breastfeeding ≥12 months	0.15	0.09	1.16	0.98–1.37	0.12
Osteocalcin (ng/mL)	0.06	0.02	1.06	1.02–1.10	0.005
Fracture History	0.77	0.3	2.16	1.20–3.90	0.01

BMI: body mass index, kg/m²: kilogram/square meter, ng/mL: nanogram/milliliter

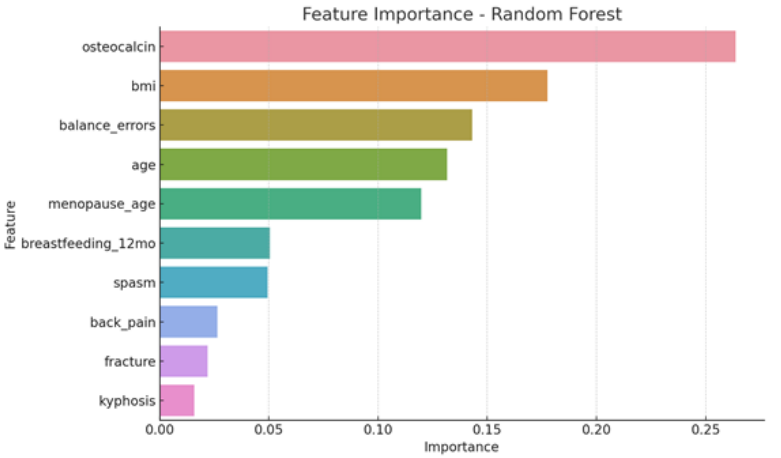

Figure 1. Feature importance for predicting osteoporosis using a Random Forest classifier. The model highlights serum osteocalcin, BMI, and dynamic balance errors as the top predictive features, followed by age, menopause age, and extended breastfeeding.

duration (≥12 months) is associated with an increased risk of postmenopausal osteoporosis (8). Our findings showed that while extended breastfeeding was significantly associated with osteoporosis in univariate analysis, it did not remain an independent predictor in multivariate logistic regression. Instead, traditional risk factors such as advanced age, low BMI, earlier menopausal age, elevated serum osteocalcin levels, and vertebral fractures demonstrated stronger independent associations (10).

A notable contribution of this study is the application of modern AI tools to a historical dataset. We implemented a Random Forest algorithm using Python and scikit-learn, incorporating clinical variables such as age, BMI, menopausal age, osteocalcin, balance errors, fracture history, and breastfeeding duration. The model demonstrated good discriminatory ability (AUC = 0.89) and identified complex interactions among variables that are difficult to detect through conventional statistical methods. This underscores the potential of AI to enhance predictive modeling in metabolic bone disorders.

Our AI-based analysis reinforces the multidimensional nature of osteoporosis risk in postmenopausal women. The high AUC and sensitivity of the Random Forest classifier under-score the clinical utility of combining hormonal (osteocalcin), anthropometric (BMI), and neuro-muscular (balance errors) variables in predictive models. Interestingly, while breastfeeding ≥12 months was statistically significant in traditional tests, its relative importance ranked sixth in AI-based modelingindicating that its predictive value is modest when adjusted for other variables. The role of osteocalcin as an independent predictor of osteoporosis in our analysis is consistent with its emerging recognition as a marker of bone turnover and metabolic activity (11-12). Likewise, the increased frequency of vertebral fractures and balance impairments among osteoporotic patients highlights the importance of fall risk assessments in this population (13-14). Impaired proprioception and

postural control increase fall risk, compounding the effects of fragile bones and accelerating the disability cascade (15).

Our study also demonstrates that AI can be meaningfully retrofitted into previously collected data, allowing for a deeper exploration of risk factor interactions and hypothesis generation. This has implications for individualized risk prediction, especially in resource-limited settings where prospective AI-enabled data collection may not be feasible.

Machine learning algorithms have become relatively mature and developed over many years in medical data processing. They possess stable and accurate detection performance, laying a solid foundation for the detection and diagnosis of osteoporosis (16). Furthermore, unsupervised algorithms like k-means clustering could have identified latent subpopulations at high risk. Clustering techniques have been applied to the diagnosis of multiple diseases including but not limited to breast cancer, Parkinson's disease, Alzheimer's disease and psychiatric disorders (17-20). It has also been known that AI-based computer vision could have enhanced vertebral fracture detection and AI-integrated clinical decision support systems might have provided real-time alerts for BMD testing referrals, as well (21,22).

Limitations include the retrospective single-center design, modest sample size, and lack of external validation for the AI model. Furthermore, breastfeeding history was self-reported, which may introduce recall bias. Nevertheless, this study provides a valuable proof of concept for how AI tools can reframe clinical interpretations and contribute to preventive strategies in women's health.

CONCLUSION

Extended breastfeeding (particularly when lasting 12 months or longer) emerges as a significant contributor to osteoporosis risk in postmenopausal women, especially when combined with early menopause and low BMI. Clinicians should consider breastfeeding history when assessing osteoporosis risk and offer nutritional counseling and preventive measures accordingly. However, it is not an independent risk factor when adjusted for more dominant predictors.

AI, if available at the time of the original study, would likely have revolutionized the analytical depth, efficiency, and clinical application of this research. It could have helped us to uncover the role and also underline the importance of osteocalcin in the diagnosis of osteoporosis. Future studies should embrace AI tools to enhance understanding of multifactorial diseases like osteoporosis and to develop more individualized, data-driven prevention strategies.

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The authors declare that they have no conflict of interest to disclose

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