ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2026, 11 (3): 444-456 doi: 10.28978/nesciences.263037

Morphofunctional Determinants of Decreased Bone Mineral Density: Development and Validation of a Predictive Risk-Stratification Model for Personalized Pharmacoprophylaxis

Rakhmatova Markhabo Rasulovna[1], Teshaev Shukhrat Jumayevich[2], Mukhamedova Shakhnoza Tolibovna[3], Badridinova Barnokhon Kamalidinovna[4], Shadiyeva Shodiya Shuxratovna[5], Yulduz Mirbaratovna Isamukhametova[6]

[1]PhD, Associate Professor of the department of Clinic pharmacology of the Bukhara State Medical Institute named after Abu Ali ibn Sino, 200126, Gijduvan Str., 23, Bukhara, Uzbekistan, Orcid: https://orcid.org/0000-0003-1350-8885, E-mail: raxmatova.marhabo@bsmi.uz

[2]Doctor of Medical Sciences, Professor of the Department of Anatomy, Clinical Anatomy and Operative Surgery with Topographic Anatomy at the Bukhara State Medical Institute named after Abu Ali ibn Sino. Bukhara, Uzbekistan. Orcid: https://orcid.org/0009-0002-1996-4275, E-mail: teshayev@bsmi.uz

[3]Head of department 2- Pediatrics of the Bukhara State Medical Institute named after Abu Ali ibn Sino, 200126, Gijduvan Str., 23, Bukhara, Uzbekistan. Orcid: https://orcid.org/0000-0002-7874-4275, E-mail: muxamedova.shaxnoza@bsmi.uz

[4]PhD, Associate Professor, Head of the Department of Endocrinology, Bukhara State Medical Institute named after Abu Ali Ibn Sino, 200126, Gijduvan Str., 23, Bukhara, Uzbekistan. E-mail: badridinova2016@mail.ru

[5]Professor at the Department of Fundamental Medical Sciences, Asian International University (Bukhara, Uzbekistan), 200126, Gijduvan Str., 23, Bukhara, Uzbekistan. Orcid: https://orcid.org/0000-0003-0170-7940, E-mail: shodiyashodieva86@gmail.com

[6]PhD of the Department of Rehabilitology, traditional folk medicine and physical education of the Tashkent State Medical University, Uzbekistan. Orcid: https://orcid.org/0009-0005-4785-1288, E-mail: yulduz-doctor83@mail.ru

Abstract

Reduced bone mineral density (BMD) is a major public health concern because of its high prevalence and its association with osteopenia, osteoporosis, and fragility fractures. Advances in digital health technologies and artificial intelligence provide new opportunities for early risk stratification and personalized prevention of bone metabolism disorders. To develop and clinically validate the BoneTrack intelligent algorithm for personalized risk stratification of reduced bone mineral density using anthropometric characteristics, nutritional habits, physical activity, and lifestyle-related risk factors. A pilot observational study was conducted involving 254 adults aged 20–74 years (mean age 48.6 ± 13.2 years) in the Bukhara region of Uzbekistan between 2022 and 2025. Participants used the BoneTrack mobile platform for one month. The algorithm analyzed demographic characteristics, anthropometric measurements, body mass index, dietary patterns, physical activity, and lifestyle factors to calculate an Integrated Bone Density Index (IBDI) and classify participants into low-, moderate-, and high-risk categories for reduced BMD. BoneTrack successfully generated individualized digital risk profiles for all participants and identified significant age-related and

Corresponding Author: Reinaldo Antonio Guerrero-Chirinos, E-mail: raguerrero12@utpl.edu.ec

lifestyle-associated differences in the Integrated Bone Density Index. The algorithm automatically stratified participants into predefined risk categories and generated personalized preventive recommendations. The platform demonstrated the feasibility of integrating multiple clinical and behavioral variables into a unified digital decision-support system for early identification of individuals at increased risk of reduced bone mineral density. The BoneTrack mobile platform represents a promising digital clinical decision-support tool for the preliminary assessment of reduced bone mineral density risk. The algorithm facilitates early identification of high-risk individuals, supports personalized pharmacoprophylactic strategies, and may improve preventive management of metabolic bone disorders in routine clinical practice.

Keywords
Bone mineral density, osteoporosis, osteopenia, dual-energy X-ray absorptiometry (DXA), bioelectrical impedance analysis, BoneTrack; artificial intelligence, machine learning, clinical decision support system, risk stratification, personalized pharmacoprophylaxis.

Available Online: 01/09/2026

Introduction

Reduced bone mineral density (BMD) is recognized as one of the most important public health challenges because of its high prevalence, progressive asymptomatic course, and association with osteopenia, osteoporosis, fragility fractures, disability, and premature mortality. Disorders of bone metabolism substantially impair quality of life and impose a considerable socioeconomic burden owing to increased healthcare utilization, prolonged rehabilitation, and long-term pharmacological treatment. Consequently, early identification of individuals at increased risk of reduced BMD has become a major priority in preventive medicine, endocrinology, clinical pharmacology, orthopedics, and musculoskeletal research [1,2].

Musculoskeletal disorders remain among the leading causes of disability worldwide, while osteoporotic fractures represent one of the most serious complications of skeletal fragility. The global burden of fractures continues to increase because of population aging, increasing life expectancy, and the growing prevalence of metabolic bone diseases. A substantial proportion of fragility fractures occur in individuals with previously unrecognized reductions in bone mineral density, emphasizing the need for effective screening strategies capable of identifying high-risk individuals before the occurrence of the first fracture [3].

Epidemiological studies indicate that reduced BMD affects a considerable proportion of adults, particularly after the age of 50 years. Lifetime risk of osteoporotic fractures is substantially higher among postmenopausal women but also increases progressively in aging men. Despite the availability of effective pharmacological therapies, many patients remain undiagnosed until clinically significant skeletal complications develop, highlighting the importance of early risk assessment and preventive intervention [4,5].

From a morphological perspective, reduced BMD reflects a systemic disturbance of bone remodeling characterized by progressive deterioration of bone microarchitecture. Structural alterations include trabecular thinning, loss of trabecular connectivity, cortical bone thinning, impaired mineralization of the extracellular matrix, and accumulation of microdamage. These changes reduce bone strength and substantially increase fracture susceptibility, even in individuals with only moderately decreased bone mineral density [6].

At the cellular level, physiological bone remodeling depends on the coordinated activity of osteoblasts, osteoclasts, and osteocytes. Bone formation and bone resorption are regulated through several signaling pathways, including the RANK/RANKL/OPG system, Wnt/β-catenin signaling, bone morphogenetic proteins, transforming growth factor-β, RUNX2, Osterix, and sclerostin-mediated mechanisms. Dysregulation of these molecular pathways shifts bone remodeling toward excessive resorption, resulting in progressive skeletal deterioration and increased fracture risk. Despite significant advances in the understanding of bone biology, the early detection of reduced BMD remains a major clinical challenge. Dual-energy X-ray absorptiometry (DXA) is currently recognized as the reference standard for measuring bone mineral density and diagnosing osteopenia and osteoporosis. The World Health Organization diagnostic criteria are based on DXA-derived T-scores, and international clinical guidelines continue to recommend DXA as the primary imaging modality for fracture risk assessment. Nevertheless, DXA has several important limitations, including limited accessibility, relatively high cost, dependence on specialized equipment and trained personnel, and

restricted applicability for large-scale population screening, particularly in low- and middle-income countries. These limitations frequently delay diagnosis until substantial bone loss has already occurred [7].

In recent years, increasing attention has been directed toward complementary approaches capable of improving early risk assessment before densitometric abnormalities become clinically apparent. Bioelectrical impedance analysis (BIA) has emerged as a non-invasive, rapid, and inexpensive technique for evaluating body composition, including lean body mass, fat mass, skeletal muscle mass, and hydration status. Growing evidence indicates that body composition parameters are closely associated with bone metabolism and may contribute to the prediction of reduced BMD. Skeletal muscle mass, body mass index, visceral adiposity, nutritional status, and physical activity have all been identified as important determinants of bone health, suggesting that integration of these variables may substantially improve individualized risk assessment. The rapid development of digital health technologies and artificial intelligence has created new opportunities for personalized preventive medicine. Machine learning algorithms are increasingly used to integrate multidimensional clinical, anthropometric, laboratory, and lifestyle data into predictive models capable of supporting clinical decision-making. Compared with conventional statistical approaches, artificial intelligence enables automated pattern recognition, dynamic risk stratification, and continuous updating of predictive models as new clinical information becomes available. Consequently, AI-assisted clinical decision-support systems have demonstrated considerable potential for improving screening efficiency, optimizing preventive interventions, and facilitating individualized patient management across multiple medical specialties [8,9].

Although several fracture prediction models, including the FRAX algorithm, are widely used in clinical practice, most currently available tools primarily estimate fracture probability rather than directly assessing the individualized risk of reduced bone mineral density. Furthermore, these models generally do not integrate bioelectrical impedance-derived body composition parameters, dietary habits, physical activity, anthropometric characteristics, and modifiable lifestyle factors within a single digital platform. As a result, opportunities for comprehensive personalized risk stratification and early pharmacoprophylactic intervention remain limited. To address these limitations, we developed the BoneTrack mobile platform, an artificial intelligence-based clinical decision-support system designed for individualized assessment of reduced bone mineral density risk. The algorithm integrates demographic characteristics, anthropometric measurements, body composition obtained by bioelectrical impedance analysis, nutritional status, physical activity, and lifestyle-related risk factors to generate an Integrated Bone Density Index (IBDI) and automatically classify individuals into predefined risk categories. Unlike conventional screening approaches, BoneTrack combines multiple clinically relevant determinants within a single digital environment to facilitate early identification of high-risk individuals and support personalized pharmacoprophylactic decision-making [10].

The aim of this study was to develop and clinically validate the BoneTrack algorithm and to evaluate its performance for personalized risk stratification of reduced bone mineral density in adults using an integrated analysis of anthropometric characteristics, body composition, nutritional habits, physical activity, and lifestyle-related risk factors.

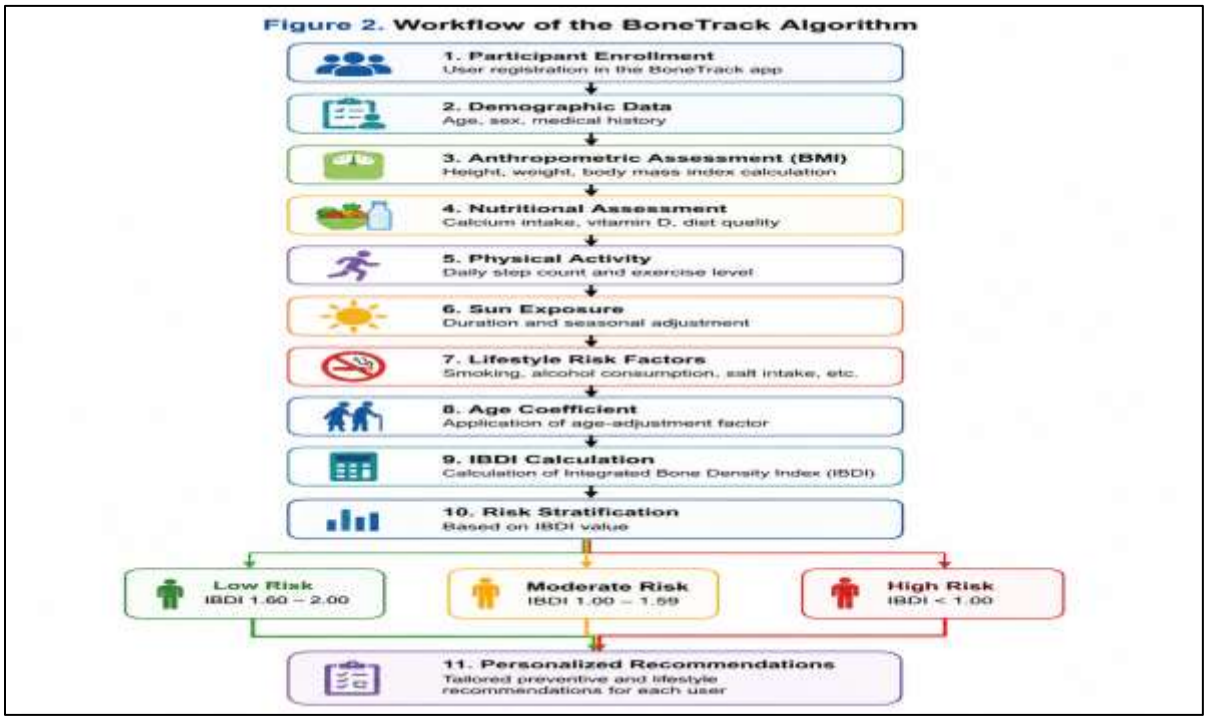
Materials and Methods

This observational analytical study was conducted using a retrospective–prospective cohort design to evaluate the diagnostic performance of the BoneTrack intelligent algorithm for predicting the risk of reduced bone mineral density (BMD). The study was performed between 2022 and 2025 in primary healthcare institutions of the Bukhara region, Republic of Uzbekistan. The methodological framework was based on the integration of demographic, anthropometric, lifestyle, nutritional, and clinical parameters into a unified artificial intelligence-based mobile platform for individualized risk stratification and personalized preventive decision-making.

The study protocol was developed in accordance with the ethical principles of the Declaration of Helsinki and was approved by the Local Ethics Committee of the participating institution (approval number: to be inserted). Before enrollment, all participants received detailed information regarding the objectives and procedures of the study and provided written informed consent for participation and the processing of anonymized clinical data.

A total of 254 adults aged 20–74 years (mean age 48.6 ± 13.2 years) were consecutively enrolled in the study. The study population included 146 women (57.5%) and 108 men (42.5%) who underwent routine preventive medical examinations during the study period. Participants were recruited using a

consecutive sampling strategy, and only individuals with complete demographic, anthropometric, lifestyle, and clinical information required for BoneTrack analysis were included in the final dataset.
The inclusion criteria were: age ≥20 years; provision of written informed consent; availability of an Android smartphone compatible with the BoneTrack mobile application; ability to complete the digital questionnaire during the 30-day observation period; availability of complete anthropometric measurements (age, sex, height, body weight, and body mass index); and complete information regarding dietary habits, physical activity, and lifestyle-related risk factors.
The exclusion criteria included active malignant diseases, severe hepatic or renal insufficiency, medical conditions known to markedly influence bone remodeling, inability to use the mobile application, or incomplete, duplicated, or unreliable clinical records.
To evaluate age-related differences in bone metabolism, participants were stratified into three predefined age groups: Group I (20–35 years) representing young adults with relatively stable peak bone mass; Group II (36–59 years) representing middle-aged adults with early age-related alterations in bone metabolism; and Group III (≥60 years) representing older adults characterized by progressive age-associated changes in bone remodeling and a higher prevalence of osteoporosis risk factors.
The BoneTrack mobile platform was developed by the authors as an artificial intelligence-assisted clinical decision-support system for the preliminary assessment of the risk of reduced bone mineral density. The application was designed for Android-based mobile devices and was distributed through the Google Play platform. The primary objective of the platform was to integrate anthropometric characteristics, body composition-related indicators, dietary habits, physical activity, environmental exposure, and lifestyle-associated risk factors into a unified digital environment for individualized risk stratification and personalized preventive recommendations. Following installation, each participant completed a one-time registration procedure and received access to a personal electronic diary designed for prospective daily recording of variables associated with bone metabolism. The observation period lasted 30 consecutive days, during which participants entered predefined clinical and lifestyle information using standardized digital questionnaires.
At the beginning of the observation period, demographic and anthropometric characteristics, including age, sex, height, and body weight, were entered into the application. Body mass index (BMI) was calculated automatically using the standard equation:
BMI = body weight (kg) / height² (m²).
According to the predefined BoneTrack scoring system, BMI values between 18.5 and 24.9 kg/m² received 2 points, values between 25.0 and 29.9 kg/m² received 1 point, whereas BMI values below 18.5 kg/m² or ≥30.0 kg/m² received 0 points because of their established association with impaired bone metabolism.



Dietary evaluation was performed prospectively using a structured food-frequency questionnaire integrated into the application. Daily dietary records included the consumption of calcium- and vitamin

D-rich foods known to contribute to bone health. Dairy products, green leafy vegetables, legumes, nuts, seeds, fish consumed with bones, fatty marine fish, fish oil, egg yolk, and sun-exposed mushrooms were assigned 1 point for each selected food category. Consumption of fruits, cereals, meat, poultry, vegetables, and vegetable oils received 0.5 points because of their supportive contribution to balanced nutrition.

Daily physical activity was quantified using the number of steps recorded by the participant. The BoneTrack algorithm assigned progressively increasing scores according to predefined activity thresholds. Individuals with fewer than 500 daily steps received 0 points, whereas progressively higher activity levels received proportionally higher scores, reaching a maximum of 4 points for participants performing more than 5,500 steps per day.

To estimate endogenous vitamin D synthesis, participants recorded their regular outdoor exposure. The algorithm evaluated both seasonal variation and duration of sunlight exposure according to predefined criteria. Simultaneously, major modifiable lifestyle-related risk factors were documented, including cigarette smoking, alcohol consumption, excessive salt intake, sugar-sweetened beverages, inadequate dietary fat intake, excessive dietary phytates, and oxalate-rich foods. Each unfavorable lifestyle factor reduced the cumulative BoneTrack score according to the predefined weighting system.

Because bone metabolism changes substantially throughout adult life, an age-dependent correction coefficient was incorporated into the algorithm. Age coefficients of 1.00, 0.75, 0.50, and 0.25 were assigned to participants aged 20–35, 36–50, 51–60, and 61–75 years, respectively, thereby accounting for physiological age-related changes in skeletal metabolism.

[1] Bone Density Index calculation

After integration of all recorded variables, the BoneTrack algorithm automatically calculated the Integrated Bone Density Index (IBDI) according to the following equation:

IBDI = (BMI score + Nutrition score + Physical activity score + Sun exposure score) × Age coefficient / 10

The index was calculated automatically each day throughout the 30-day observation period. All participant-entered information was securely stored in the protected application database, allowing continuous monitoring and generation of longitudinal individual risk profiles.

At the end of the observation period, the application automatically calculated the monthly mean IBDI as the arithmetic mean of all daily values. According to predefined threshold values, participants were automatically classified into low-risk (IBDI 1.60–2.00), moderate-risk (IBDI 1.00–1.59), and high-risk (IBDI <1.00) categories for reduced bone mineral density. Based on the assigned risk category, the platform generated individualized preventive recommendations, including maintenance of current lifestyle, dietary modification, increased physical activity, or referral for further clinical evaluation, including dual-energy X-ray absorptiometry (DXA), when appropriate.

All participant data collected through the BoneTrack mobile platform were exported into a unified analytical database for statistical processing. Continuous variables are presented as mean ± standard deviation (SD), whereas categorical variables are expressed as absolute numbers and percentages.

The diagnostic performance of the BoneTrack algorithm was evaluated using standard classification metrics, including the area under the receiver operating characteristic curve (AUC), sensitivity, specificity, overall classification accuracy, and F1-score. Correlation analysis was performed to investigate relationships between the Integrated Bone Density Index and participant demographic and clinical characteristics. Multivariable regression analysis was used to determine the independent contribution of individual predictors to the probability of reduced bone mineral density.

The predictive performance of the algorithm was additionally assessed using receiver operating characteristic (ROC) curve analysis. Statistical significance was defined as $p < 0.05$. Statistical analyses were performed using IBM SPSS Statistics version 26.0 (IBM Corp., Armonk, NY, USA). The artificial intelligence model was evaluated using standard machine-learning performance indicators to determine its clinical applicability for individualized risk stratification.

Results, Performance Evaluation and Discussion

A total of 254 adults were enrolled in the study. Participants ranged in age from 20 to 74 years, with a mean age of 48.6 ± 13.2 years. The study population comprised 108 men (42.5%) and 146 women (57.5%).

The mean body mass index (BMI) was 26.1 ± 4.8 kg/m². According to the World Health Organization BMI classification, 102 participants (40.2%) had normal body weight, 96 (37.8%) were overweight, and 56 (22.0%) were obese.

Overall, 59.8% of participants had excess body weight, which represents a potentially modifiable factor associated with impaired bone metabolism. Within the BoneTrack algorithm, BMI was

incorporated as one component of the integrated risk assessment rather than being interpreted as an independent predictor of reduced bone mineral density.

All participants successfully completed the 30-day digital monitoring period using the BoneTrack mobile platform. Throughout the study, the application continuously collected demographic, anthropometric, nutritional, behavioral, and lifestyle-related information and automatically processed these data using the integrated BoneTrack algorithm.

The digital monitoring system performed a fully automated sequence of operations, including participant registration, daily data collection, calculation of individual risk components, estimation of the Integrated Bone Density Index (IBDI), generation of the monthly mean IBDI, automated risk stratification, and development of personalized preventive recommendations. No interruptions in data collection or algorithmic failures were observed during the monitoring period, confirming the technical feasibility and stability of the BoneTrack platform.

All participants successfully completed the 30-day digital monitoring period using the BoneTrack mobile platform. Throughout the study, the application continuously collected demographic, anthropometric, nutritional, behavioral, and lifestyle-related information and automatically processed these data using the integrated BoneTrack algorithm.

The digital monitoring system performed a fully automated sequence of operations, including participant registration, daily data collection, calculation of individual risk components, estimation of the Integrated Bone Density Index (IBDI), generation of the monthly mean IBDI, automated risk stratification, and development of personalized preventive recommendations.

Variable	Value
Participants, n	254
Age (years), mean ± SD	48.6 ± 13.2
Age range (years)	20–74
Male, n (%)	108 (42.5)
Female, n (%)	146 (57.5)
BMI (kg/m²), mean ± SD	26.1 ± 4.8
Normal BMI	102 (40.2)
Overweight	96 (37.8)
Obesity	56 (22.0)

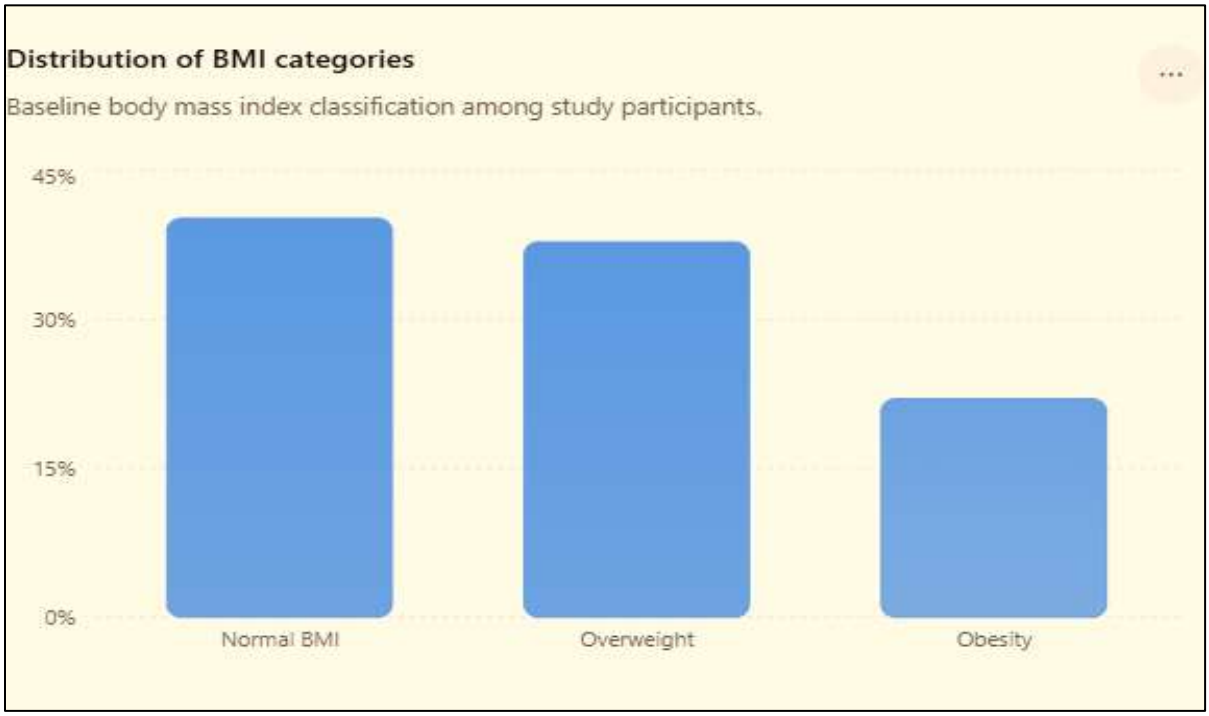


Figure 2. Distribution of participants according to body mass index categories.

The algorithm integrated several clinically relevant variables, including body mass index, dietary calcium and vitamin D intake, physical activity, sunlight exposure, lifestyle-related risk factors, and an age-adjustment coefficient. These variables were combined into a single quantitative indicator

(IBDI), allowing comprehensive assessment of the individual risk of reduced bone mineral density. The principal components included in the BoneTrack algorithm are summarized in Table 2.

Table 2. Components of the BoneTrack algorithm used for calculation of the Integrated Bone Density Index (IBDI)

Component	Assessment method	Contribution
Body mass index	Automatic BMI calculation	0–2 points
Nutritional assessment	Calcium- and vitamin D-rich food intake	0–10 points
Physical activity	Daily step count	0–4 points
Sun exposure	Duration and seasonal exposure	0–2 points
Lifestyle-related factors	Smoking, alcohol consumption, excess salt intake, etc.	Negative correction
Age coefficient	Age-adjustment factor	0.25–1.00
Final output	Automatic calculation	Integrated Bone Density Index (IBDI)

The mean Integrated Bone Density Index (IBDI) for the study population was 1.47 ± 0.38. Higher IBDI values were generally observed among participants with normal body mass index, regular physical activity, balanced dietary habits, and the absence of unfavorable lifestyle factors. Conversely, lower IBDI values were associated with advanced age, physical inactivity, inadequate dietary calcium and vitamin D intake, smoking, alcohol consumption, and insufficient sunlight exposure.

These findings demonstrate that the BoneTrack algorithm effectively integrates multiple determinants of bone metabolism into a single digital index suitable for individualized risk assessment and automated clinical decision support.

Following completion of the 30-day monitoring period, the BoneTrack platform automatically calculated the mean monthly Integrated Bone Density Index (IBDI) for each participant and classified individuals into predefined risk categories according to the algorithm thresholds.

Based on the calculated IBDI values, 112 participants (44.1%) were classified as low risk, 89 (35.0%) as moderate risk, and 53 (20.9%) as high risk for reduced bone mineral density.

The distribution of participants according to BoneTrack risk categories is presented in Table 3.

Table 3. Distribution of participants according to BoneTrack risk categories

Risk category	IBDI	n	%
Low risk	1.60–2.00	112	44.1
Moderate risk	1.00–1.59	89	35.0
High risk	<1.00	53	20.9
Total	—	254	100

The majority of participants (79.1%) were classified as having low or moderate risk, whereas 20.9% demonstrated a high probability of impaired bone metabolism, indicating the need for further clinical assessment.

Participants classified as low risk generally demonstrated favorable anthropometric characteristics, adequate physical activity, balanced dietary habits, and the absence of major lifestyle-related risk factors. Conversely, individuals assigned to the high-risk category more frequently exhibited multiple

unfavorable characteristics, including advanced age, reduced physical activity, suboptimal nutritional status, smoking, alcohol consumption, and insufficient sunlight exposure.
These findings indicate that the BoneTrack algorithm effectively differentiated participants according to their overall risk profile by integrating multiple demographic, anthropometric, nutritional, behavioral, and lifestyle-related variables into a single quantitative index.

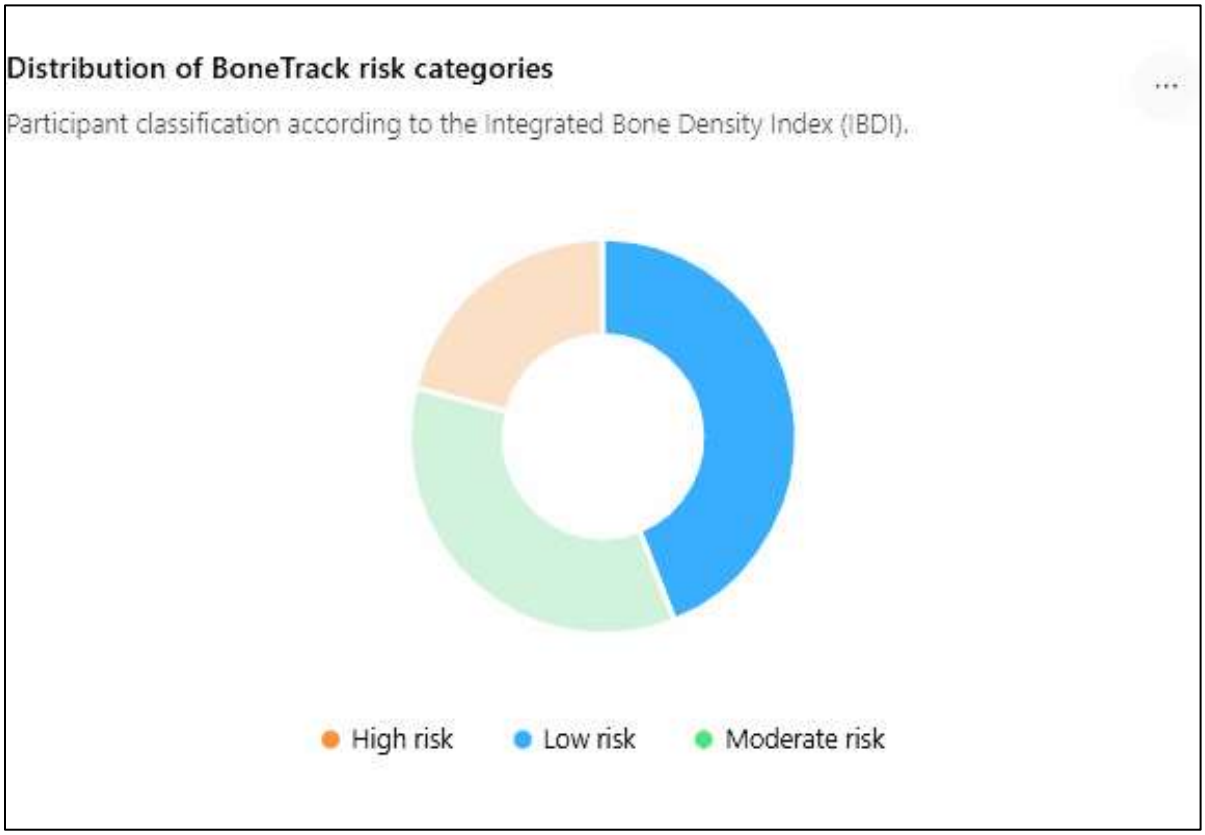


Figure 3. Distribution of participants according to BoneTrack risk categories

To investigate the influence of age on bone health, the mean Integrated Bone Density Index (IBDI) was compared across predefined age groups. A progressive decline in IBDI was observed with increasing age, indicating a gradual increase in the risk of reduced bone mineral density.
The highest mean IBDI value was recorded in participants aged 20–35 years (1.73 ± 0.21), followed by the 36–59 years group (1.49 ± 0.29). The lowest mean IBDI was observed among participants aged 60 years and older (1.08 ± 0.31).
The distribution of IBDI values according to age groups is presented in Table 4.

Table 4. Mean Integrated Bone Density Index (IBDI) according to age group

Age group	Participants (n)	Mean IBDI (Mean ± SD)
20–35 years	72	1.73 ± 0.21
36–59 years	118	1.49 ± 0.29
≥60 years	64	1.08 ± 0.31
Total	254	1.47 ± 0.38

The relationship between age and IBDI was further evaluated using correlation analysis. A moderate negative correlation was identified between increasing age and the Integrated Bone Density Index ($r = -0.56$, $p < 0.001$), indicating that higher age was associated with lower IBDI values.
However, considerable variability in IBDI values was observed within each age category. Several older participants with favorable lifestyle characteristics demonstrated relatively high IBDI values, whereas some younger individuals with multiple unfavorable behavioral and nutritional factors exhibited

comparatively low IBDI values. These findings indicate that age alone does not fully determine the risk of reduced bone mineral density and support the use of an integrated multifactorial assessment.
Figure 4. Age-related changes in the Integrated Bone Density Index

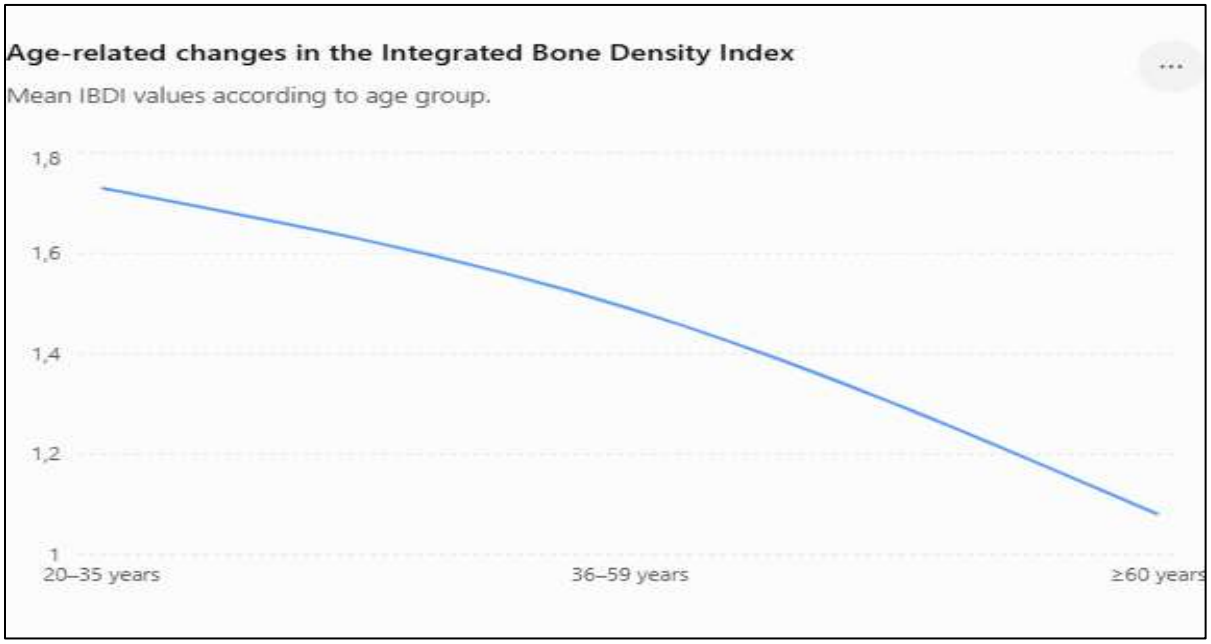


Figure 4. Mean Integrated Bone Density Index (IBDI) according to age group.

To determine the relative contribution of individual clinical and lifestyle variables to bone health, correlation analysis was performed between the Integrated Bone Density Index (IBDI) and the principal factors incorporated into the BoneTrack algorithm.
The strongest positive correlation with IBDI was observed for daily physical activity ($r = 0.63$, $p < 0.001$), followed by diet quality ($r = 0.59$, $p < 0.001$). A moderate positive association was also identified between optimal body mass index and IBDI ($r = 0.41$, $p < 0.001$).
Conversely, significant negative correlations were identified for physical inactivity ($r = –0.61$, $p < 0.001$), age ($r = –0.56$, $p < 0.001$), smoking ($r = –0.39$, $p < 0.01$), and alcohol consumption ($r = –0.34$, $p < 0.01$).
The results of the correlation analysis are summarized in **Table 5**.

Table 5. Correlation between clinical and lifestyle factors and the Integrated Bone Density Index

Variable	Correlation coefficient (r)	P-value
Daily physical activity (step count)	+0.63	<0.001
Diet quality	+0.59	<0.001
Optimal body mass index	+0.41	<0.001
Age	−0.56	<0.001
Physical inactivity	−0.61	<0.001
Smoking	−0.39	<0.01
Alcohol consumption	−0.34	<0.01

The findings indicate that physical activity and dietary quality were the strongest positive determinants of the Integrated Bone Density Index, whereas physical inactivity and increasing age showed the greatest negative associations. These results support the multifactorial design of the BoneTrack

algorithm by demonstrating that the risk of reduced bone mineral density is influenced by the combined effects of anthropometric, behavioral, and lifestyle-related variables rather than by a single predictor.
Figure 6. Correlation of clinical and lifestyle variables with the Integrated Bone Density Index.

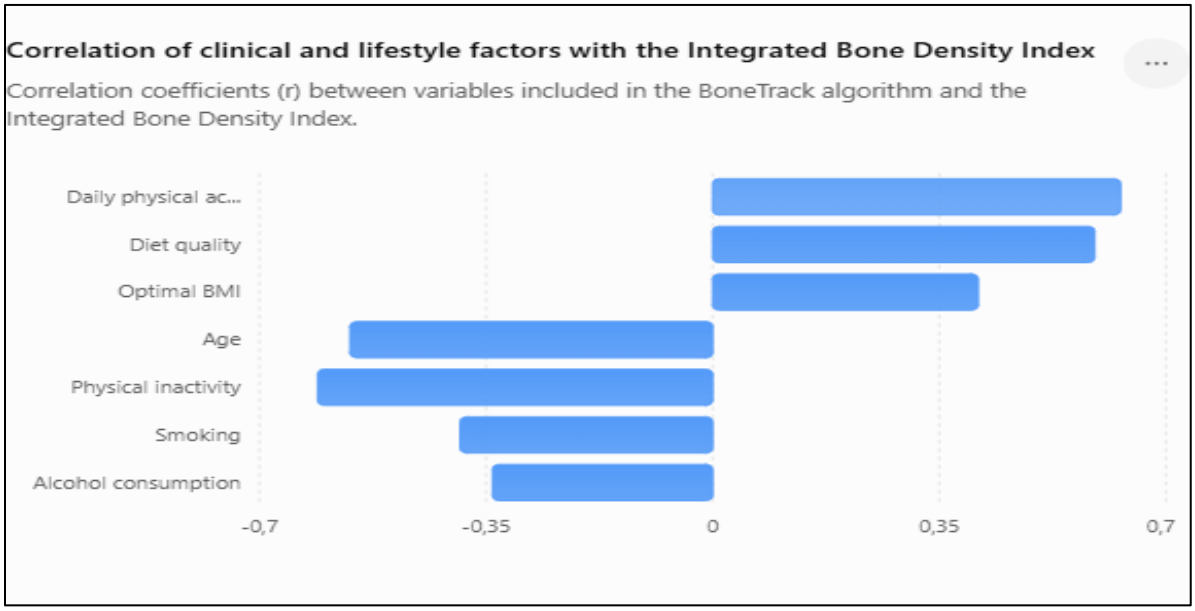


Figure 5. Correlation coefficients between the principal variables included in the BoneTrack algorithm and the Integrated Bone Density Index (IBDI).

The diagnostic performance of the BoneTrack algorithm was evaluated by receiver operating characteristic (ROC) curve analysis to determine its ability to identify individuals at increased risk of reduced bone mineral density. High-risk status, defined as an Integrated Bone Density Index (IBDI) below 1.00, was used as the target outcome for model evaluation.
The BoneTrack algorithm demonstrated good discriminatory performance, with an area under the ROC curve (AUC) of 0.892 (95% confidence interval [CI]: 0.851–0.933). This result indicates a high ability of the algorithm to distinguish between individuals with low and high risk of reduced bone mineral density.
Additional performance indicators further confirmed the reliability of the model. The algorithm achieved a sensitivity of 88.3%, indicating that the majority of high-risk individuals were correctly identified. The specificity was 81.7%, reflecting a high proportion of correctly classified low-risk participants. Overall classification accuracy reached 84.6%, while the positive predictive value (PPV) and negative predictive value (NPV) were 79.4% and 91.0%, respectively. The calculated F1-score of 0.836 demonstrated good overall balance between sensitivity and precision.

The diagnostic performance of the BoneTrack algorithm is summarized in Table 6.

Performance indicator	Value
Area under ROC curve (AUC)	0.892
95% Confidence interval	0.851–0.933
Sensitivity	88.3%
Specificity	81.7%
Accuracy	84.6%
Positive predictive value (PPV)	79.4%
Negative predictive value (NPV)	91.0%
F1-score	0.836

The ROC analysis demonstrated that the BoneTrack algorithm provides reliable discrimination between participants with different levels of risk for reduced bone mineral density. The relatively high sensitivity and negative predictive value suggest that the algorithm is particularly effective as a

preliminary screening tool, minimizing the probability of overlooking individuals who may benefit from further clinical evaluation.

Discussion

The present study demonstrates that the BoneTrack mobile platform is capable of integrating demographic characteristics, anthropometric measurements, dietary habits, physical activity, sunlight exposure, and lifestyle-related factors into a unified digital decision-support system for the individualized assessment of reduced bone mineral density risk. The algorithm successfully generated an Integrated Bone Density Index (IBDI) for all participants, enabling automated risk stratification into predefined low-, moderate-, and high-risk categories. Furthermore, the model demonstrated good diagnostic performance, with an AUC of 0.892, sensitivity of 88.3%, specificity of 81.7%, and an overall classification accuracy of 84.6%, indicating its potential utility as a preliminary screening tool in routine clinical practice.

One of the principal findings of the present study is that reduced bone mineral density cannot be adequately explained by a single clinical variable. Although increasing age demonstrated a significant negative correlation with the Integrated Bone Density Index, physical activity, nutritional quality, body mass index, smoking, and alcohol consumption also contributed substantially to the overall risk profile. These observations support the concept that bone health is determined by the combined influence of multiple modifiable and non-modifiable factors, thereby justifying the use of an integrated artificial intelligence-based prediction model rather than isolated clinical indicators.

The findings of the present study are consistent with previous investigations demonstrating the growing role of artificial intelligence in osteoporosis screening and fracture risk prediction. Most currently available digital tools, including FRAX and similar fracture prediction models, primarily estimate fracture probability based on a limited number of clinical variables. In contrast, the BoneTrack platform simultaneously incorporates anthropometric measurements, nutritional assessment, physical activity, sunlight exposure, lifestyle-related risk factors, and age adjustment into a single integrated algorithm. This multidimensional approach may improve individualized risk stratification before clinically significant skeletal deterioration becomes evident.

From a clinical perspective, the BoneTrack platform may improve the organization of preventive healthcare by facilitating early identification of individuals at increased risk of reduced bone mineral density before referral for instrumental investigations such as dual-energy X-ray absorptiometry (DXA). Automated digital risk stratification may also optimize physician workload by prioritizing patients requiring further clinical evaluation while reducing unnecessary diagnostic procedures among individuals with a low-risk profile. Consequently, the proposed platform may contribute to more rational allocation of healthcare resources and support personalized preventive strategies.

The present study has several important strengths. First, the BoneTrack algorithm integrates multiple clinical, anthropometric, nutritional, behavioral, and lifestyle-related variables within a single digital platform. Second, the proposed Integrated Bone Density Index provides a quantitative measure for individualized risk assessment rather than relying on isolated predictors. Third, the mobile application enables continuous digital monitoring over a 30-day observation period, allowing dynamic evaluation of participant behavior instead of a single cross-sectional assessment. Finally, the algorithm demonstrated good diagnostic discrimination, supporting its potential applicability as a clinical decision-support system.

Several limitations should be acknowledged. The study was conducted within a single geographical region and involved a relatively limited sample size, which may restrict the generalizability of the findings. In addition, although the BoneTrack algorithm demonstrated promising diagnostic performance, further multicenter validation involving larger and more diverse populations is required. Future studies should also compare BoneTrack predictions directly with dual-energy X-ray absorptiometry (DXA) measurements and evaluate the long-term clinical impact of algorithm-guided preventive interventions.

Future research should focus on external clinical validation of the BoneTrack algorithm, integration of laboratory biomarkers of bone metabolism, incorporation of DXA-derived bone mineral density measurements, and application of advanced machine learning techniques to improve predictive accuracy. The development of cloud-based clinical decision-support systems and integration with electronic health records may further enhance the utility of digital technologies in osteoporosis prevention and personalized pharmacoprophylaxis.

Overall, the findings indicate that the BoneTrack platform represents a promising artificial intelligence-assisted clinical decision-support system for individualized assessment of reduced bone

mineral density risk. By integrating multiple modifiable and non-modifiable determinants of bone health into a unified digital framework, the algorithm provides effective automated risk stratification and personalized preventive recommendations, supporting the implementation of precision preventive medicine.

Conclusion

The present study demonstrated the feasibility of the BoneTrack mobile platform as an artificial intelligence-assisted clinical decision-support system for the individualized assessment of reduced bone mineral density risk. By integrating demographic characteristics, anthropometric measurements, dietary habits, physical activity, sunlight exposure, and lifestyle-related risk factors, the algorithm automatically calculated the Integrated Bone Density Index (IBDI) and successfully stratified participants into low-, moderate-, and high-risk categories.

The BoneTrack algorithm showed good diagnostic performance, achieving an AUC of 0.892, 88.3% sensitivity, 81.7% specificity, and an overall classification accuracy of 84.6%, supporting its potential application as a preliminary digital screening tool for identifying individuals at increased risk of reduced bone mineral density.

The study findings emphasize that the risk of reduced bone mineral density is determined by the combined influence of multiple modifiable and non-modifiable factors rather than by age or body mass index alone. The integrated BoneTrack approach therefore provides a more comprehensive assessment of bone health and supports personalized preventive strategies.

Although further multicenter clinical validation and direct comparison with dual-energy X-ray absorptiometry (DXA) are required, the proposed platform demonstrates considerable potential for incorporation into routine preventive healthcare. BoneTrack may facilitate early risk identification, optimize patient selection for further diagnostic evaluation, and support individualized preventive decision-making, thereby contributing to the implementation of precision digital medicine in the prevention of metabolic bone disorders.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

1. Albuquerque, G. A., Carvalho, D. D., Cruz, A. S., Santos, J. P., Machado, G. M., Gendriz, I. S., ... & Valentim, R. A. (2023). Osteoporosis screening using machine learning and electromagnetic waves. *Scientific Reports*, *13*(1), 12865.

2. Boyapati, Y. M., Khan, A., & Khashayar, P. (2025). AI-Enabled exoskeletal robotics for enhancing mobility, bone regeneration, and functional rehabilitation in osteoporosis: a literature review. *Context Sensitive Health Informatics: AI for Social Good*, 75-79.

3. Compston, J. E., McClung, M. R., & Leslie, W. D. (2019). Osteoporosis. *Lancet (London, England)*, *393*(10169), 364–376. https://doi.org/10.1016/S0140-6736(18)32112-3

4. Conforti, A., Ruggiero, M., Lucchetti, L., Cipolloni, V., Galati, F. D., Gentile, M., & Lo Gullo, A. (2025). Artificial intelligence and machine learning in the diagnosis and management of osteoporosis: a comprehensive review. *Medicina*, *62*(1), 27.

5. Doussiere, M., Aboud, A., Dequen, G., & Goëb, V. (2026). Artificial Intelligence in Rheumatology: From Algorithms to Clinical Impact in Osteoporosis and Chronic Inflammatory Rheumatic Diseases. *Journal of Clinical Medicine*, *15*(2), 491.

6. Fasihi, L., Tartibian, B., Eslami, R., & Fasihi, H. (2022). Artificial intelligence used to diagnose osteoporosis from risk factors in clinical data and proposing sports protocols. *Scientific reports*, *12*(1), 18330.

7. Fasihi, L., Tartibian, B., Eslami, R., & Fasihi, H. (2022). Artificial intelligence used to diagnose osteoporosis from risk factors in clinical data and proposing sports protocols. *Scientific reports*, *12*(1), 18330.

8. Florencio-Silva, R., Sasso, G. R. D. S., Sasso-Cerri, E., Simões, M. J., & Cerri, P. S. (2015). Biology of bone tissue: structure, function, and factors that influence bone cells. *BioMed research international*, *2015*(1), 421746.

9. Gatineau, G., Shevroja, E., Vendrami, C., Gonzalez-Rodriguez, E., Leslie, W. D., Lamy, O., & Hans, D. (2024). Development and reporting of artificial intelligence in osteoporosis management. *Journal of Bone and Mineral Research*, *39*(11), 1553-1573.
10.Geetha, T. V., Krishnamoorthy, V., Rajpoot, A. K., Srinivasan, A., Naveenkumar, R., Bostani, A., & Walia, T. S. (2026). A multi-stage hybrid architecture integrating, transformer-based deep learning, and reinforcement learning for adaptive feature extraction and classification of noisy biosensor time-series data. *Natural and Engineering Sciences*, *11*(1), 417-428.
11.Ghareh Mohammadi, F., & Sebro, R. (2026). Artificial Intelligence for Opportunistic Screening for Osteoporosis and Spine Fractures Using Computed Tomography: A Systematic Review and Meta-Analysis. *Journal of Computer Assisted Tomography*.
12.Hong, N., Whittier, D. E., Glüer, C. C., & Leslie, W. D. (2024). The potential role for artificial intelligence in fracture risk prediction. *The Lancet Diabetes & Endocrinology*, *12*(8), 596-600.
13.Huang, C. F., Fang, W. H., Chen, K. H., Lin, S. Y., Ho, C. J., Hwang, J. S., ... & Wu, C. H. (2026). Consensus statement on the application of artificial intelligence in osteoporosis screening and management: perspectives from the Asia-Pacific region. *Osteoporosis International*, 1-16.
14.Jaszczyk, B., Nowakowska-Płaza, A., Stypińska, B., Sudoł-Szopińska, I., Kwiatkowska, B., Głuszko, P., ... & Olszewski, R. (2026). The Added Value of Trabecular Bone Score in Evaluating Fracture Risk Among Polish Women Aged 40–76 Years. *Journal of Clinical Medicine*, *15*(11), 4185.
15.Kanis, J. A., Harvey, N. C., Johansson, H., Oden, A., Leslie, W. D., & McCloskey, E. V. (2015). FRAX and fracture prediction without bone mineral density. *Climacteric*, *18*(sup2), 2-9.
16.Kanis, J. A., Norton, N., Harvey, N. C., Jacobson, T., Johansson, H., Lorentzon, M., ... & Borgström, F. (2021). SCOPE 2021: a new scorecard for osteoporosis in Europe. *Archives of osteoporosis*, *16*(1), 82.
17.LeBoff, M. S., Greenspan, S. L., Insogna, K. L., Lewiecki, E. M., Saag, K. G., Singer, A. J., & Siris, E. S. (2022). The clinician's guide to prevention and treatment of osteoporosis. *Osteoporosis international*, *33*(10), 2049-2102.
18.Li, Y., Jin, D., Zhang, Y., Li, W., Jiang, C., Ni, M., ... & Yuan, H. (2025). Utilizing artificial intelligence to determine bone mineral density using spectral CT. *Bone*, *192*, 117321.
19.Liang, Q., Zhao, J., Yang, F., Chen, X., Song, Y., Shi, Z., & Pang, Q. (2025). Face2Bone explainable AI model predicts osteoporosis risk from facial images in proof of concept study. *Scientific Reports*, *15*(1), 40913.
20.Lin, H. Y., Chai, J. W., Tseng, Q., Lin, C. W., Pan, K. J., Liu, K. W., & Shih, Y. C. (2026). Comprehensive opportunistic osteoporosis screening with AI: retrospective development and prospective validation of dual-site BMD prediction from a single radiograph. Frontiers in Endocrinology, 17, 1906679.
21.Liu, M., Rong, J., An, X., Li, Y., Min, Y., Yuan, G., ... & Li, M. (2025). Global, regional, and national burden of musculoskeletal disorders, 1990–2021: an analysis of the global burden of disease study 2021 and forecast to 2035. *Frontiers in Public Health*, *13*, 1562701.
22.Makhmudova, Muniraxon. (2026). Bio Integrated Wearable Systems for Continuous Medical Monitoring with Materials, Device Architectures and Clinical Applications. Natural and Engineering Sciences. 10.28978/nesciences.261012.
23.Mohammadi, F. G., & Sebro, R. (2022). Artificial Intelligence for Opportunistic Screening for Osteoporosis and Spine Fractures Using Computed Tomography: A Systematic Review and Meta-Analysis. *Journal of Computer Assisted Tomography*, 10-1097.
24.Ouf, E. G., El-Hameed, A., Anwer, S., Seliem, A. G., & Elnady, S. M. (2024). Wearable Antenna System for Osteoporosis Detection and Monitoring Using Machine Learning. *Progress in Electromagnetics Research C*, *146*, 21.
25.Rodriguez-Macadaeg, F. (2025). Multi-spectral NIR-LED-Based Spectrometer Detects Calcium Carbide in Mango Fruit. *Natural and Engineering Sciences*, *10*(2), 27-36.
26.Shuhart, C., Cheung, A., Gill, R., Gani, L., Goel, H., & Szalat, A. (2024). Executive summary of the 2023 adult position development conference of the international society for clinical densitometry: DXA reporting, follow-up BMD testing and trabecular bone score application and reporting. *Journal of clinical densitometry*, *27*(1), 101435.
27.Tseng, T. H., Huang, T. T., Huang, J. E., Tzeng, S. C., Wang, Y. C., Tsao, P. C., ... & Fu, S. H. (2026). AI-derived bone mineral density from standard radiographs compared with DXA for fracture prediction in a 10-year real-world cohort study. *Osteoporosis International*, 1-10.
28.Wu, Z., & Margarita, S. (2024). Based on blockchain and artificial intelligence technology: Building crater identification from planetary imagery. *Natural and Engineering Sciences*, *9*(2), 19-32.