Journal of Bone and Mineral Research, 2026, **41**, 136–142
https://doi.org/10.1093/jbmr/zjaf194
Advance access publication: December 18, 2025
Research Article

Spine age derived from DXA vertebral fracture assessment images predicts incident fractures and mortality: the Manitoba Bone Mineral Density Registry

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Abstract

Biological age may better predict health outcomes than chronological age by capturing individual heterogeneity in aging. We investigated whether accelerated spine aging, estimated from DXA vertebral fracture assessment (VFA) using deep learning, predicts fracture and mortality independently of age, vertebral fracture (VF), and BMD. A convolutional neural network model to estimate age from lateral spine radiographs was trained in a Korean cohort (VERTE-X, $n = 10\,341$). Among 27 601 adults aged ≥50 who underwent DXA VFA in Manitoba, Canada (2010-2023), the pre-trained model was fine-tuned to DXA VFA images using 20% randomly sampled subset. Among remaining 80% set, test set included 8810 individuals who completed DXA before 2017 as the outcomes were ascertained through 2018. Predicted spine age difference (PAD = spine age-chronological age) was calculated in the test set. During a mean follow-up of 3.9 yr, 899 incident fractures and 969 deaths occurred. Spine age positively correlated with chronological age (r = 0.89), with a mean difference of 0.0 yr (SD = 3.4). Factors associated with higher PAD include VFs (+1.02 yr), nonvertebral fracture history (+0.22), generalized spine structural artifacts (+1.45), smoking (+1.20), and lower FN BMD (+0.60 per T-score decrement), collectively explaining 66% of PAD variance. Each SD increase in PAD was associated with higher risk of any (adjusted hazard ratio = 1.11), nonvertebral (1.10), major osteoporotic (1.12), and hip fracture (1.25), and mortality (1.12), independent of covariates (all $p < .05$). In summary, accelerated spine aging detected from DXA VFA predicts fracture and mortality risk independently of age, clinical risk factors, VF, spine structural artifacts, and BMD in individuals at high risk of fracture, supporting its potential to enhance fracture risk assessment.

Keywords: aging, spine age, X-ray, DXA, biological age

Lay Summary

This study investigated whether accelerated spine aging, estimated from DXA vertebral fracture assessment (VFA) using deep learning, predicts fracture and mortality in 27 601 adults aged ≥50 who underwent DXA VFA in Manitoba, Canada. The accelerated spine age was associated with greater fracture risk and mortality, independent of chronological age, clinical risk factors, prevalent vertebral fracture (VF), spine structural artifacts, and FN BMD, supporting its potential to enhance fracture risk assessment.

Introduction

Aging is a major risk factor that drives the increase in fracture risk and mortality.[1–3] The association between age and fracture remains independent after adjustment for strong predictors, such as BMD, at the hip or spine.[4–6] Based on the observation that individuals do not age at the same pace in functional or physiological aspects, biological age is increasingly thought to be a more potent risk factor for various health outcomes than chronological age.[7,8]

Measurements of biological age have been developed using diverse data, including clinical phenotypes, epigenomic, or transcriptomic profiles.[9,10] Studies using image data, such as retinal photographs or facial images, to estimate the biological

Received: July 23, 2025. **Revised:** October 24, 2025. **Accepted:** December 6, 2025

age of various organs and systems have shown promising results.[11,12] To enhance fracture risk assessment, a strategy to utilize lateral spine radiographs or DXA vertebral fracture assessment (DXA VFA) images as a source to estimate biological age could have a clinical advantage, as these are widely used in the standard screening and assessment process for osteoporosis.[13]

We developed a convolutional neural network (CNN) model to estimate spine age using a large Korean lateral spine radiograph database. Accelerated spine age (higher predicted age difference (PAD) between spine age and chronological age) was associated with a higher risk of fracture and mortality in a cohort of community-dwelling older Korean adults.[14] As an extension of these findings, we hypothesized that the CNN model could capture common features of accelerated spine aging that are related to fracture and mortality risk in populations with different ethnicities and image modalities. If proven, this would strengthen the generalizability of the CNN model in detecting accelerated aging across individuals of various ethnicities, while providing insight into fundamental features of musculoskeletal aging in spine images.

In this study, we investigated the association of accelerated spine age, estimated from DXA VFA images, with fracture and mortality risk in individuals aged 50 yr or older who underwent routine DXA testing through the Manitoba BMD Program.

Materials and methods

Manitoba BMD Registry

The Manitoba BMD Registry maintains population-based data of all examinations covering clinical DXA services for the Province of Manitoba, Canada.[15] Vertebral fracture assessment testing has been included in DXA assessment (Lunar Prodigy or iDXA, GE Healthcare) since 2010 for individuals who had T-score of ≤ -1.5 (minimum at the LS, TH, or FN) and (1) age ≥ 70 yr; (2) age 50-69 yr; and historical height loss >5 cm, or measured height loss >2.5 cm, or glucocorticoid exposure for at least 3 mo over the past year. Deidentified data from individuals in the Manitoba BMD Registry were linked to province-wide healthcare administrative databases using an anonymized personal health identification number. Two primary care databases (the Physician Claims Database [PCD] and Discharge Abstract Database [DAD]) were used to obtain information on health care visits. Physician Claims Database provided information including the date, types of services, and diagnostic codes using the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes. The study was approved by the University of Manitoba Human Research Ethics Board (HREB HS21018, H2004:017M) and data access was granted by the Manitoba Health Information Privacy Committee (HIPC 2016/2017-2029). This study adhered to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines for reporting cohort studies.

Spine age estimation

In our prior work, we trained a CNN model to predict chronological age from lateral spine radiographs in the VERTE-X (VERTEbral fracture and osteoporosis detection in spine X-ray) cohort of Korean adults who underwent spine examination in an institution (mean age 63.6 yr; 64.3% women; Table S1).[14] VERTE-X spine age model was developed using the EfficientNet-B4 architecture, with output logits corresponding to ages from 40 to 100 yr, allowing it to cover a wide age distribution (Figure S1).[14] During training, a mean-variance loss function, including softmax, mean, and variance losses, was applied to optimize categorical age prediction, align the predicted mean with the chronological age, and constrain the spread of the predicted distribution, respectively. The final predicted age was computed as the expected value of the SoftMax-normalized probability distribution (Figure S2). To apply VERTE-X spine age model to DXA VFA images, a fine-tuning process was performed using a randomly sampled 20% subset of the Manitoba BMD Registry VFA images (Figure S3). To ensure consistent image quality across VFA images, the images underwent preprocessing including normalization, resizing, and intensity scaling (Figure S4). Details of preprocessing and model fine-tuning process can be found in the supplementary methods. Predicted age difference was calculated as spine age minus chronological age. A higher PAD was considered indicative of accelerated spine aging. We applied the Gradient-weighted Class Activation Mapping (Grad-CAM) technique to visualize the regions of DXA VFA images that contributed most to the model's age prediction.[16]

Covariates

Statistical models were adjusted for multiple covariates that are indicative of increased fracture risk, including chronological age, sex, BMI, current smoking status, high alcohol intake (alcohol substance abuse diagnosis codes in earlier year), prolonged oral corticosteroid use (>90 d dispensed in the 1 yr prior to DXA), rheumatoid arthritis, parental hip fracture, secondary osteoporosis, diabetes mellitus, DXA VFA morphologic vertebral fracture (VF) detected using modified algorithm-based qualitative (mABQ) method,[17] localized or generalized spine structural artifact, and FN BMD T-score based on the young White female reference from the Third National Health and Nutrition Examination Survey (NHANES III).[18] Localized spine structural artifact was defined as the presence of any excluded vertebral body in LS BMD report due to variation of T-score (>1.0) between adjacent vertebral bodies. Generalized spine structural artifact was defined as a missing LS BMD value, resulting from either an unperformed test or unreportable results due to degenerative changes or surgical prostheses affecting multiple vertebral levels (Figure S5).

Outcomes

The primary outcome was the occurrence of any clinical fracture during follow-up, excluding skull, fingers, toes, ankles, and hospitalized high-trauma fractures. Secondary outcomes include non-vertebral, major osteoporotic (composite of vertebral, forearm, hip, and humerus), and hip fractures, and all-cause mortality. Fracture diagnoses and procedures up to March 31, 2018 were coded using the ICD-9-CM prior to 2004, and the Canadian version of the Tenth Revision (ICD-10-CA) from 2004 onward. Fractures were identified using radiologically validated algorithms that have been adopted for national surveillance purposes.[19,20] Fractures resulting from high-trauma events, which were excluded, were identified using trauma-specific ICD codes.

Statistical analysis

Clinical characteristics of study individuals were compared between event and non-event groups using the 2-sample independent *t*-test for continuous variables and the chi-square test for categorical variables. Beheshti method was applied for bias adjustment.[21] Agreement between predicted spine age and chronological age was assessed using Bland–Altman plots,[22] with examining heteroscedasticity of residuals using the Breusch–Pagan/Cook–Weisberg test.[23,24] Multivariable linear regression models were fit to investigate the factors associated with PAD. Areas under the receiver operating characteristic curves (AUROCs) for discriminating outcomes were compared between spine age and chronological age using the DeLong method. Age- and sex-adjusted Cox regression models were used to plot the cumulative incidence of outcomes by PAD quartiles. Cox proportional hazard models were fitted to test associations between PAD (per one SD increment) and all outcomes, with or without adjustment for covariates. To examine potential effect modification, interaction terms between PAD and chronological age, as well as between PAD and the presence of VF at baseline, were included in the Cox proportional hazards models. As a sensitivity analysis, we applied the Fine–Gray subdistribution hazards model to assess the robustness of the association between PAD and fracture, accounting for death as a competing risk.[25] No violation of the proportional hazard assumption was observed. Statistical significance was assessed using 2-sided tests with $\alpha = .05$. SPSS for Windows version 29.0 (IBM) and Stata 18.0 (StataCorp) were used for analysis.

Results

Clinical characteristics of study individuals

Out of the 27 601 VFA scans performed between 2010 and 2023 in Manitoba, 20% ($n = 5537$) were used to fine-tune the VERTE-X spine age model (Figure S2). Among remaining 80% subset, data of 8810 individuals were analyzed as the test set after excluding those undergoing DXA after 2017 (as outcome was collected through 2018) and those 50 yr or younger. The mean age of individuals in the test set was 75.3 yr, with a range between 50 and 99 yr, and 93.2% were women. Individuals with fracture events during follow-up ($n = 899$) had older age, lower BMI, higher prevalence of high alcohol intake, prior fracture, local or general spine structural artifacts, and lower DXA BMD T-scores (Table 1).

Correlation between spine age and chronological age

A modest positive correlation was observed between spine age derived from DXA VFA images and chronological age (Pearson correlation coefficient 0.89, $p < .001$). The mean PAD was +0.0 yr, with SD of 3.4 yr, and followed a normal distribution (Figure S6). In Bland–Altman plot (Figure S7), 95% limit of agreement of PAD across mean of spine and chronological age was −7.2 to 6.2. Test for heteroscedasticity did not reach statistical significance ($p = .993$).

Factors associated with predicted spine age difference

Figure 1 shows DXA VFA images of women with identical chronological ages (70 yr) but varying predicted spine ages (53, 70, and 79 yr). Grad-CAM visualization indicated that the model primarily focused on features across multiple vertebral levels to predict spine age. In a multiple linear regression model, various factors were associated with PAD (Table 2). Factors associated with PAD included generalized spine structural artifacts (+1.45 yr), current smoking status (+1.20 yr), presence of VF (+1.02 yr), localized spine structural artifacts (+0.46 yr), or history of nonvertebral fracture (+0.22 yr). Lower FN BMD was associated with higher PAD (+0.56 yr per 1 T-score decrement). The model explained 66% of the total variance of PAD (adjusted R^2 0.66).

Association of accelerated spine age with fracture and mortality

The mean follow-up duration was 3.9 ± 2.2 yr. Fracture and mortality occurred in 899 (26.4 cases per 1000 person-years) and 969 (28.4 cases per 1000 person-years) individuals during follow-up, respectively (Table S2). Compared with chronological age, spine age showed consistently higher AUROC for discriminating all outcomes including hip fracture (0.72 vs 0.70) and mortality (0.70 vs 0.68; $p < .001$ for all; Table S3). When participants were stratified by PAD <-3.4 yr (1 SD below the mean; decelerated spine age), −3.4 to 3.4 (normal), and >3.4 (1 SD above the mean; accelerated spine age) groups, accelerated spine age group had greater fracture and mortality risk compared to the decelerated group (p-for-trend $<.001$ for all outcomes; Figure 2). In unadjusted Cox proportional hazard model, each 1 SD increase in PAD was associated with a higher risk of any fracture (aHR 1.22, 95% CI 1.14-1.30) and mortality (aHR 1.18, 95% CI 1.11-1.25). The association remained robust (fracture: aHR 1.11, 95% CI 1.04-1.19; mortality: aHR 1.12, 95% CI 1.05-1.20) in multivariable model adjusted for age, sex, BMI, high alcohol intake, current smoking, chronic glucocorticoid use, rheumatoid arthritis, parental history of hip fracture, secondary osteoporosis, the presence of diabetes mellitus, prevalent VFs, clinical history of nonvertebral fractures, spine structural artifacts, and FN BMD in the fully adjusted model (Table 3; Table S4). No significant interaction was observed between PAD and chronological age (p for interaction = .417). In the fully-adjusted Fine–Gray competing risk model, the association between PAD and fracture remained robust after accounting for death as a competing event (aHR 1.11, 95% CI 1.04-1.19, $p = .002$). When analysis was restricted to individuals without prevalent vertebral at baseline, PAD remained as a robust predictor of incident fracture (aHR 1.11, 95% CI 1.03-1.21, $p = .008$) in fully adjusted model. Prevalent VF at baseline did not significantly modify the association between PAD and the risk of incident fracture (p for interaction = .862).

Discussion

In this study, spine age was estimated using DXA VFA images using a pre-trained CNN that was fine-tuned in a large clinical cohort of adults undergoing DXA screening in Manitoba, Canada. Although the mean absolute difference between predicted spine age and chronological age was minimal (0.3 yr), the variability of the difference was substantial (SD 5.6 yr). As expected, the presence of VFs or spine structural artifacts on DXA VFA images, as well as low bone density at the hip, was associated with higher PAD, indicative of accelerated spine aging. Clinical risk factors, such as current smoking status and a history of clinical nonvertebral fractures, were also

Table 1. Demographic and clinical characteristics of study participants.

Characteristic	Overall ($n = 8810$)	Incident fracture		p-value
		No ($n = 7911$)	Yes ($n = 899$)	
Age, yr	75.3 ± 6.8	75.1 ± 6.7	77.3 ± 7.4	<.001
Women	8275 (93.2)	7976 (93.2)	839 (93.3)	.920
BMI, kg/m^2	26.2 ± 5.0	26.3 ± 5.0	25.4 ± 4.6	<.001
Current smoking	718 (8.2)	635 (8.0)	83 (9.2)	.211
High alcohol intake	22 (0.3)	15 (0.2)	7 (0.8)	.048
Chronic glucocorticoid use	522 (5.9)	466 (5.9)	56 (6.2)	.684
Rheumatoid arthritis	385 (4.3)	338 (4.3)	47 (5.2)	.219
Parent hip fracture	1121 (12.7)	996 (12.6)	125 (13.9)	.279
Secondary osteoporosis	1448 (16.4)	1299 (16.4)	149 (16.6)	.906
Diabetes mellitus	1132 (12.9)	1022 (12.9)	110 (12.2)	.562
Previous fracture history				
Vertebral	1460 (16.6)	1212 (15.3)	248 (27.6)	<.001
Non-vertebral	2361 (26.8)	2011 (25.4)	350 (38.9)	<.001
Spine structural artifacts				
Localized	2512 (28.5)	2225 (28.1)	287 (31.9)	.020
Generalized	1096 (12.4)	1006 (12.7)	90 (10.0)	.012
DXA BMD FN T-score	−2.1 ± 0.7	−2.0 ± 0.7	−2.2 ± 0.6	<.001

Data are presented as n (%) or mean ± SD.

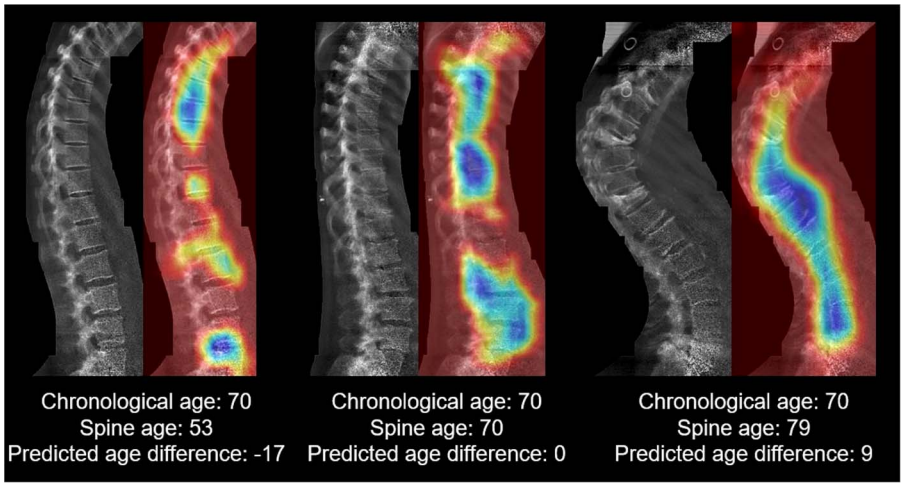

Figure 1. Examples of DXA VFA images of women with identical chronological age but varying predicted spine age. Right panel (chronological age 70, spine age 79, and predicted age difference +9) indicates an image with features of accelerated spine aging.

associated with increased PAD. Higher PAD was associated with greater risks of fracture and mortality, independent of clinical risk factors, VF, spine structural artifacts, and BMD.

The accelerated spine age derived from spine images using a CNN (the VERTE-X spine age model) was associated with fracture and mortality in a cohort of community-dwelling Korean older adults.[14] In a hold-out test set of the Korean cohort, spine age estimated from lateral spine radiographs using the VERTE-X model showed an average difference of −0.8 yr compared to chronological age (SD 4.9), with better predictive performance for the presence of morphologic VF or osteoporosis than chronological age.[14] The preliminary findings could be successfully replicated and extended in a large cohort of Canadian adults who had screening DXA tests. Through the fine-tuning strategy, the knowledge of the pre-trained model to extract core features of aging from spine images could be effectively transferred to spine images generated by different modalities (lateral spine radiographs to DXA VFA) in individuals with different ethnicities (Koreans to Canadians). These findings support the existence of common, machine-recognizable features of musculoskeletal aging in spine images, independent of image modalities, across different ethnic groups. This would provide an important basis to set effective strategies to develop more generalizable machine learning models that work on various spine image domains and population with ethnic differences, while reducing unnecessary efforts to train each model separately from scratch.

Aging is known to affect all structures of spinal units, including bones, disks, nerve fibers, ligaments, facets, and muscles.[26] Various factors contributed to accelerated spine age derived from DXA VFA images. As predicted, the presence of morphologic VFs, local or generalized spine structural artifacts, and low bone density were factors that contributed to accelerated spine age, similarly with the findings in the Korean dataset.[14] Structural artifacts of spine and current smoking were associated with the accelerated spine age. Degenerative changes of spine, one of the major cause of structural artifacts of spine, are known to increase with aging, which may accompany low back pain in older adults that limit

Table 2. Factors contributing to accelerated spine aging.

Variables	Age- and sex-adjusted		Multivariable adjusted	
	Beta coefficient[a] (95% CI)	*p*-value	Beta coefficient[a] (95% CI)	*p*-value
Generalized spine structural artifacts	1.17 (0.96-1.39)	<.001	1.45 (1.24-1.67)	<.001
Current smoking status	1.61 (1.35-1.87)	<.001	1.20 (0.95-1.45)	<.001
Vertebral fracture in DXA VFA image[b]	1.28 (1.09-1.47)	<.001	1.02 (0.83-1.21)	<.001
Women (vs men)	0.71 (0.43-0.99)	<.001	0.87 (0.59-1.15)	<.001
Femoral neck BMD, per 1 T-score decrement	0.84 (0.74-0.95)	<.001	0.60 (0.49-0.70)	<.001
Localized spine structural artifacts	0.18 (0.02-0.33)	.029	0.46 (0.30-0.61)	<.001
Previous clinical nonvertebral fracture	0.40 (0.24-0.56)	<.001	0.22 (0.06-0.37)	.006
BMI	−0.11 (−0.12 to −0.09)	<.001	−0.09 (−0.11 to −0.08)	<.001
Chronological age	0.00 (−0.12 to 0.01)	.825	−0.02 (−0.03 to −0.01)	<.001
High alcohol intake	1.30 (−0.13 to 2.72)	.074	0.64 (−0.72 to 2.00)	.360
Secondary osteoporosis	0.05 (−0.15 to 0.24)	.645	0.04 (−0.14 to 0.22)	.670
Diabetes Mellitus	−0.21 (−0.42 to 0.01)	.058	0.04 (−0.17 to 0.24)	.740
Rheumatoid arthritis	0.18 (−0.16 to 0.53)	.299	0.01 (−0.33 to 0.35)	.972
Prolonged oral corticosteroid use	−0.04 (−0.35 to 0.27)	.782	−0.02 (−0.32 to 0.28)	.916
Parental hip fracture	−0.04 (−0.25 to 0.17)	.720	−0.12 (−0.33 to 0.08)	.240

[a]Estimated beta coefficients indicate the predicted age difference (in years) for clinical characteristics. Positive beta coefficients (PAD > 0) indicate that the factor contributed to accelerated spine aging. [b]Vertebral fractures in DXA VFA images were detected using modified algorithm-based qualitative method by expert interpreters. Abbreviations: DXA VFA, DXA vertebral fracture assessment.

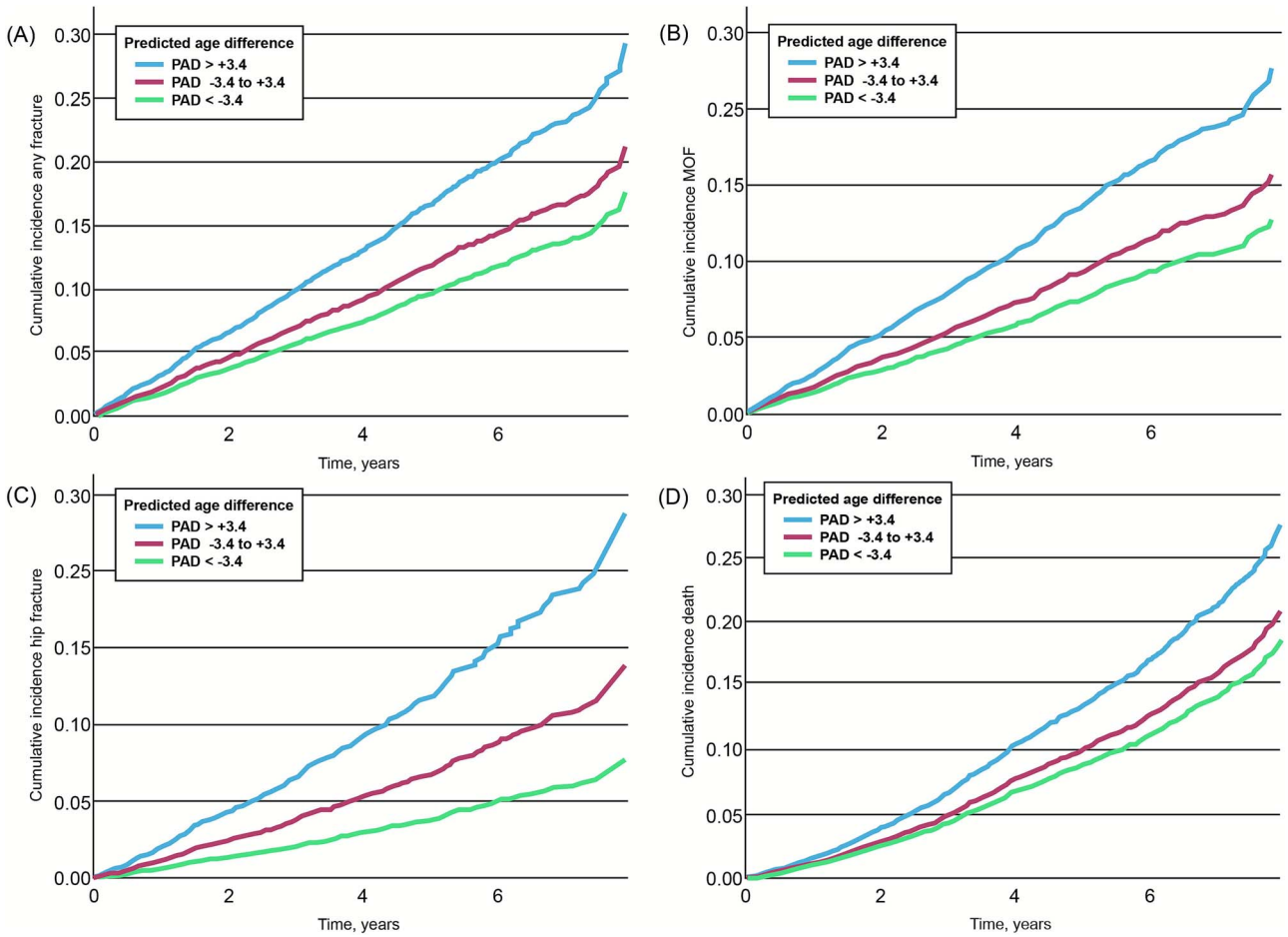

Figure 2. Age- and sex-adjusted cumulative incidence curves for (A) any incident fracture, (B) major osteoporotic fracture, (C) hip fracture, and (D) death, stratified by predicted age difference (PAD <−3.4 yr [1 SD], −3.4 to 3.4 yr, and PAD >3.4 yr).

physical performance.[26,27] In a recent study, the presence of VF was associated with worsening of degenerative changes of spine.[28] These findings align with the contribution of degenerative changes to accelerated spine age, suggesting that the coexistence of VF and degenerative change could reflect the duration and severity of age-related deformation of the spine. The adverse effect of smoking on bone density and fracture risk is well recognized.[29] Smoking is also associated with

Table 3. Association of predicted spine age difference with incident fracture and mortality.

	Model 1 (unadjusted)		Model 2 (adjusted for clinical risk factors, DXA VFA vertebral fracture, clinical nonvertebral fracture, and spine structural artifacts)		Model 3 (Model 2 + FN BMD)	
Outcomes	HR (95% CI)	*p*-value	HR (95% CI)	*p*-value	HR (95% CI)	*p*-value
Any fracture	1.22 (1.14-1.30)	<.001	1.14 (1.07-1.22)	<.001	1.11 (1.04-1.19)	.002
Nonvertebral	1.21 (1.13-1.30)	<.001	1.13 (1.05-1.22)	.001	1.10 (1.03-1.19)	.008
MOF	1.41 (1.31-1.52)	<.001	1.15 (1.07-1.24)	<.001	1.12 (1.03-1.20)	.005
Hip fracture	1.42 (1.26-1.59)	<.001	1.32 (1.17-1.50)	<.001	1.25 (1.10-1.41)	.001
Mortality	1.18 (1.11-1.25)	<.001	1.15 (1.08-1.23)	<.001	1.12 (1.05-1.20)	<.001

Hazard ratio (HR) per 1 SD increment in predicted age difference (predicted minus chronological age). Clinical risk factors: chronological age, sex, BMI, alcohol intake, current smoking status, prolonged glucocorticoid use, rheumatoid arthritis, parental hip fracture, secondary osteoporosis, and presence of diabetes mellitus. Abbreviations: VFA, vertebral fracture assessment; MOF, major osteoporotic fracture.

intervertebral disk degeneration, which may have provided visual clues to the spine age model to detect accelerated spine age in smokers.[30] Nevertheless, one third of the variance in the predicted spine age difference remained unexplained yet. Several unmeasured factors could have affected the predicted spine age including changes in body shapes, facets, ligaments, curvature of spinal axis, vascular calcification, or medical implants in organs other than bone; this needs to be investigated further.

Accelerated spine age was associated with greater fracture risk and mortality. These associations were independent of chronological age, clinical risk factors, presence of VF, degenerative changes of spine, and bone density, suggesting that the machine learning-predicted spine age could be a useful measurement to improve fracture risk assessment. This approach has unique property that summarizes a complex, multi-dimensional aging status of spine and surrounding tissues into a score on an interpretable scale, age. In clinical aspect, predicted spine age of an individual could be used to enhance the performance of risk assessment tools for fracture or other health outcomes, by adjusting chronological age using the predicted spine age difference. In preliminary results from the KURE cohort, the substitution of chronological age with spine age to calculate FRAX hip fracture probability improved the discriminatory performance for hip fracture.[14] This hypothesis needs additional investigation.

Overall fracture incidence was similar (24.1 vs 26.4 per 1000 person-years) Between the Korean derivation set (VERTE-X) and the Manitoba BMD Registry. However, VF incidence was higher in the Korean cohort, likely reflecting case definition: the Korean cohort captured both clinical and morphometric VFs, whereas the Manitoba registry captured VFs based on diagnosis codes. This also aligns with relatively higher incidence of VF reported in Korean population.[31] Non-VFs including hip were more frequent in the Manitoba cohort, which may partly relate to differences in age distribution between 2 cohorts. Despite these incidence differences, the spine age model demonstrated comparable prognostic performance across cohorts.

This study has several limitations. As an observational study, this study cannot establish that the accelerated spine age caused incident fractures or mortality directly. As we did not have measurement of true biological aging in spine yet, we used chronological age as target variable to train for the CNN model. Therefore, it was inevitable that prediction error and true accelerated spine aging in our findings could not be discerned. However, even with this limitation, we observed robust association of PAD with fracture and mortality risk independent of chronological age, sex, and other covariates.

In summary, the accelerated spine age was associated with greater fracture risk and mortality in individuals at high risk of fracture, independent of chronological age, clinical risk factors, prevalent VF, spine structural artifacts, and FN BMD. Whether utilizing the predicted spine age could enhance the predictive performance of risk assessment tools merits further investigation.

Acknowledgments

The authors acknowledge the Manitoba Centre for Health Policy for use of data contained in the Manitoba Population Research Data Repository (HIPC 2016/2017-2029). The results and conclusions are those of the authors and no official endorsement by the Manitoba Centre for Health Policy, Manitoba Health, Seniors and Active Living, or other data providers is intended or should be inferred. Data used in this study are from the Manitoba Population Research Data Repository housed at the Manitoba Centre for Health Policy, University of Manitoba and were derived from data provided by Manitoba Health and Shared Health. This article has been reviewed and approved by the members of the Manitoba Bone Density Program Committee.

Author contributions

Sang Wouk Cho (Conceptualization, Software, Methodology, Formal analysis, Investigation, Visualization, Writing—original draft, Writing—review & editing), Namki Hong (Conceptualization, Methodology, Formal analysis, Investigation, Project administration, Writing—original draft, Visualization, Writing—review & editing), Barret A. Monchka (Data curation, Methodology, Formal analysis, Writing—review & editing), Douglas Kimelman (Writing—review & editing), Steven R. Cummings (Conceptualization, Project administration, Resources, Writing—review & editing), and William D. Leslie (Conceptualization, Project administration, Data curation, Formal analysis, Investigation, Visualization, Resources, Writing—original draft, Writing—review & editing)

Supplementary material

Supplementary material is available at *Journal of Bone and Mineral Research* online.

Funding

The study was supported from the Rady Innovation Fund, Rady Faculty of Health Sciences, University of Manitoba, the Korea Health

Technology R&D Project through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health and Welfare, Republic of Korea (Grant Numbers HI22C0452 and RS-2023-00265620), and the National Research Foundation of Korea (NRF) grant funded by the Korea government (Ministry of Science and ICT, South Korea) (Grant Number RS-2023-00231864).

Conflicts of interest

All authors declare that there are no conflicts of interest.

Data availability

Data sharing is not permitted under the Researcher Agreement with Manitoba Health and Seniors Care (MHASC). However, researchers may apply for data access through the Health Research Ethics Board for the University of Manitoba and the Provincial Health Research Privacy Committee of MHASC.

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Journal of Bone and Mineral Research, 2026, 41, 136–142
https://doi.org/10.1093/jbmr/zjaf194
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