Original Paper

Real-World Deployment of a Web-Based Bone Health Self-Assessment Tool in Thailand: Descriptive Cross-Sectional Study

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Abstract

Background: Public-facing digital self-assessment tools may provide a low-barrier way for individuals to engage with preventive health information outside clinical encounters. In osteoporosis, however, real-world use of such tools and the characteristics represented among completed assessments remain incompletely described.

Objective: This study aimed to describe the real-world deployment of a public-facing web-based bone health self-assessment tool in Thailand and characterize the demographic, clinical, and lifestyle-related information captured in completed assessments. Exploratory analyses examined app-generated outputs, co-occurring unfavorable self-reported factors, and the sensitivity of descriptive findings to probable repeat assessments.

Methods: We conducted a retrospective cross-sectional study of eligible completed assessments generated during routine public use of the Bone Health Score (developed by Rathapoom Suwanaratana) web app from October through December 2025. The completed assessment was the primary unit of analysis because formal identity verification was not performed. Questionnaire data included demographic characteristics, fracture-related factors, glucocorticoid exposure, and lifestyle behaviors. The app generated a user-facing Bone Health Score, personalized recommendations, and a guideline-informed dual-energy X-ray absorptiometry (DXA) consideration prompt. Analyses were descriptive. Sensitivity analysis evaluated probable repeat assessments and alternative assumptions for the DXA-consideration prompt.

Results: A total of 256 completed assessments were included. The mean age was 51.9 (SD 14.0) years, and 195/256 (76.2%) recorded female sex. The median Bone Health Score was 110 (IQR 90-120). Among 254 assessments with recorded sex, the DXA-consideration prompt was triggered in 94 (37%). Of these, 50/94 (53.2%) occurred below the sex-specific age threshold because at least one captured non-age criterion was present. DXA-prompt sensitivity estimates were 93/226 (41.2%) after excluding default menopause responses and 95/254 (37.4%) after removing the additional early-menopause age restriction. An exploratory 8-factor unfavorable self-reported factor count identified at least 2 factors in 151/256 (59%) assessments, although this proportion varied when individual components were removed. Eighteen repeated-nickname groups were identified, including 8 high-probability repeat clusters. Retaining only the first assessment from these clusters yielded 243 assessments, with principal descriptive estimates remaining similar.

Conclusions: Routine deployment of a public-facing bone health self-assessment tool captured structured clinical and lifestyle-related information and translated it into individualized rule-based outputs. Non-age clinical factors contributed substantially

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to DXA-consideration prompts, showing that the deployed rule-based logic incorporated information beyond age alone. Further evaluation of usability, downstream behavior, clinical follow-up, and linkage with objective assessment is needed to define the broader public health role of this approach.

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KEYWORDS

osteoporosis; digital health; web-based self-assessment; public health informatics; real-world deployment; bone health

Introduction

Osteoporosis is an important public health concern in Thailand, where the disease may remain clinically silent until a fragility fracture occurs or evaluation is prompted by recognized risk factors [1,2]. Current Thai guidance emphasizes clinical fracture-risk assessment and bone mineral density measurement by dual-energy X-ray absorptiometry (DXA) for individuals who meet age- or risk-based indications [2]. Access to DXA is not uniform across the health system, particularly outside tertiary care. Recent Thai studies have highlighted limited DXA availability in primary and secondary care, together with practical barriers related to cost and feasibility for broader population assessment [3,4]. This setting creates a rationale for complementary, low-barrier approaches that allow individuals to engage with bone health information outside conventional clinical encounters.

Digital health platforms offer a flexible way to deliver health information and self-management support beyond face-to-face care, and web- and mobile-based approaches are increasingly used across chronic diseases [5]. Real-world engagement with these platforms varies across populations. Digital health literacy is associated with age, educational level, income, and social support [6], while usability, infrastructure, digital skills, privacy concerns, and perceived usefulness also influence adoption among older adults [7].

Digital approaches in osteoporosis now span education, lifestyle and self-management support, risk assessment, and treatment-related functions [8,9]. Published evaluations have commonly focused on specific technologies and selected study populations, including assessments of usability and acceptability in patients with established osteoporosis [10] and feasibility or medication-management outcomes in clinic-based populations [11]. Public-facing digital tools create a different implementation context, in which use occurs through voluntary public access rather than structured research recruitment or clinical enrollment. From a public health informatics perspective, the profile represented among completed assessments, the health information captured during routine use, and the distribution of system-generated outputs can provide a practical view of real-world deployment. These aspects have been less frequently described in osteoporosis-related digital health research.

The Bone Health Score (developed by Rathapoom Suwanaratana) web app was developed as a Thai-language, public-facing self-assessment tool that collects self-reported demographic, clinical, and lifestyle-related information and provides rule-based feedback on bone health. This study aimed to describe the real-world deployment of the app and to characterize the demographic, clinical, and lifestyle-related information represented in completed assessments. Exploratory analyses examined the distribution of app-generated outputs, the co-occurrence of unfavorable self-reported factors, and the sensitivity of descriptive findings to probable repeat assessments.

Methods

Study Design and Reporting Framework

This study was a retrospective cross-sectional study of completed assessments generated during the real-world deployment of a public-facing web-based bone health self-assessment tool in Thailand. The study was descriptive and exploratory. Reporting was guided by the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) statement for cross-sectional studies [12] (Multimedia Appendix 1) and applicable items from the CHERRIES (Checklist for Reporting Results of Internet E-Surveys) [13] (Multimedia Appendix 2).

Study Setting, Deployment, and Eligibility

The web app was developed and deployed by the Orthopedic Department of Chulabhorn Hospital, Chulabhorn Royal Academy, Bangkok, Thailand. During routine public deployment, the app was accessible through hospital communication channels, including official social media posts and QR codes displayed in the outpatient department. Access was open and voluntary and did not require registration, authentication, or membership in a predefined sampling frame. The defined study period was October 9 through December 20, 2025, and the analytic eligibility criteria included completed assessments submitted during routine public use by adults aged 20 years or older.

The analytic dataset was reconstructed from the complete app database export. Records were screened according to submission timestamps and eligibility criteria. During the retrospective data audit, the app developer confirmed that the nicknames “test,” “Test,” and “Tester” had been used by the project team for internal app testing during early deployment. Records bearing these nicknames were identified after trimming whitespace and applying case-insensitive matching. The resulting 40 in-period records were excluded independently of questionnaire responses and app-generated scores. Because access was self-directed, the analytic sample represented a convenience sample of completed assessments.

Web App and Assessment Workflow

The Bone Health Score was a responsive Thai-language web app accessible on smartphones and desktop devices without

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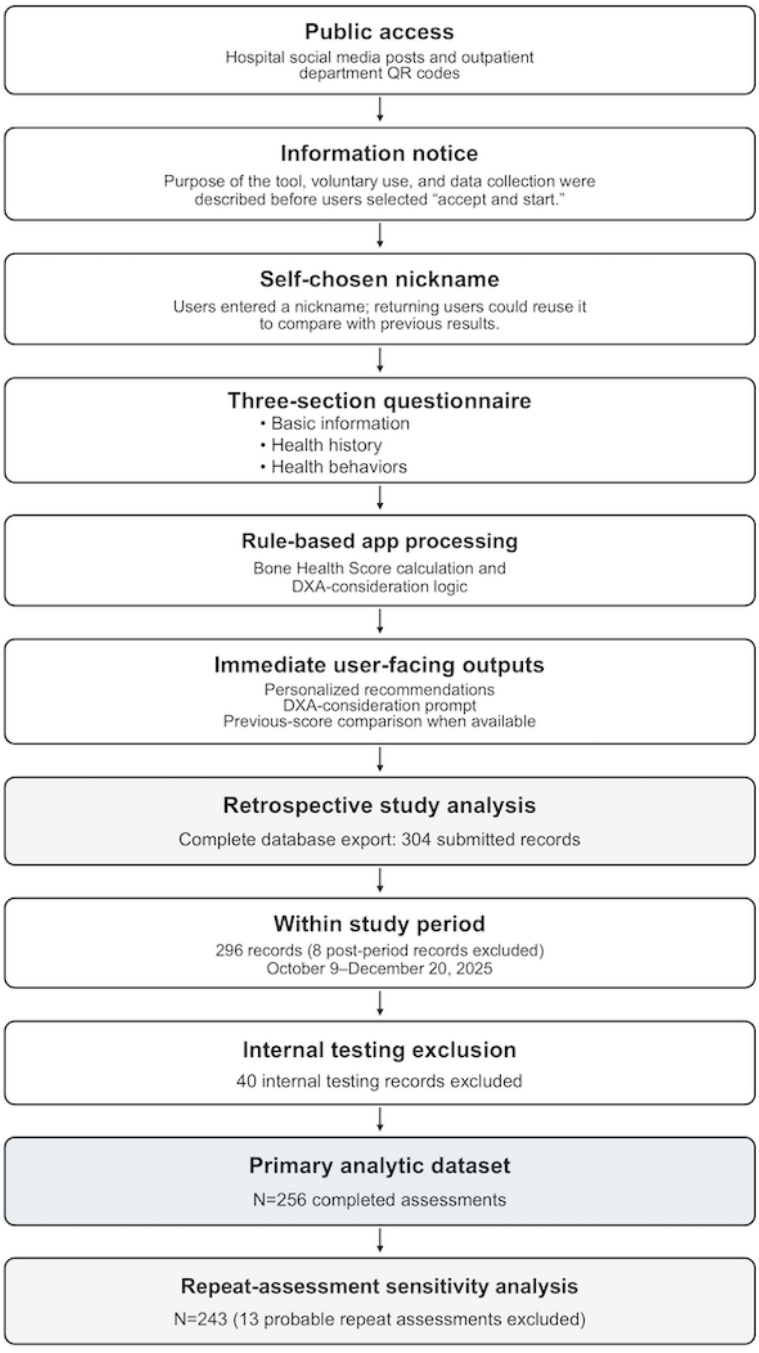
installation. Before beginning the assessment, users viewed an information notice and proceeded by selecting an “accept and start” button. Users then entered a self-chosen nickname. No authenticated registration was required, and returning users could reuse the same nickname to view their previous Bone Health Scores for longitudinal comparison. When an entered nickname already existed, the interface asked whether the nickname belonged to the current user. A user who chose to proceed could access the score-history display without a password, secondary secret, authenticated account, or device-bound token. The history display retrieved prior Bone Health Scores and submission dates associated with that nickname; it did not display the full questionnaire responses.

The assessment proceeded through 3 sequential questionnaire screens covering basic information, health history, and health behaviors. Items were presented in a fixed order. The menopause-before-age-45 item was displayed conditionally to women aged 45 to 64 years and initially showed a preselected “not yet menopausal” response, which could remain unchanged without active selection. Users could return to earlier screens and modify responses before final submission. After submission, predefined rule-based logic generated personalized recommendations, the Bone Health Score with its user-facing interpretation category, and a DXA-consideration prompt when applicable. Representative screenshots of the web app, including the landing page, health behavior and lifestyle questionnaire, and results page, are provided in Multimedia Appendix 3. The results interface also displayed a percentile based on the current score relative to previously stored app assessments. The percentile was calculated as the percentage of prior assessment records with a lower final score, rounded to the nearest whole number. Assessments with equal scores were not counted as lower, and repeated submissions were not excluded from the reference set. Because the reference set evolved as new assessments were submitted and was not population-based, percentile values were treated as a nonnormative app display and were not analyzed as a study outcome. The overall app and study workflow are shown in Figure 1.

A database record became available for analysis only after submission of the final questionnaire screen and execution of the score-calculation process. Partially completed or abandoned assessments were therefore not available in the study database. Unique visitor counts and assessment-initiation denominators were also unavailable, and CHERRIES view, participation, and completion rates could not be calculated [13]. Although several questionnaire fields were configured as required within the interface, complete cross-step validation was not enforced. Age, weight, and height were entered as numeric fields. The interface specified an allowable age range of 1 to 120 years and positive values for weight and height, but no additional cross-step plausibility-range validation was enforced. The exported dataset was reviewed for missing and implausible numeric values. No records were excluded on the basis of numeric plausibility screening. Variable-specific denominators were used where applicable.

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Figure 1. Web app and study workflow. Users accessed the public-facing app through hospital social media posts or outpatient department QR codes, reviewed an information notice, entered a self-chosen nickname, and completed a 3-section questionnaire. The app generated rule-based outputs, including the Bone Health Score, personalized recommendations, and a DXA-consideration prompt. The complete database export contained 304 submitted assessment records. Eight records submitted outside the defined study period (October 9-December 20, 2025) and 40 internal testing records were excluded, leaving 256 eligible completed assessments for the primary analysis. No additional records were excluded for age younger than 20 years (n=0) or on the basis of numeric plausibility review (n=0). The completed assessment was used as the primary unit of analysis because individual identities were not verified. A repeat-assessment sensitivity analysis excluded 13 probable repeat submissions, retaining 243 assessments.



Questionnaire Variables

The questionnaire collected demographic, anthropometric, clinical, and lifestyle-related information. Basic information included age, sex, weight, and height, from which BMI was calculated. Health-history items included parental hip fracture, self-reported low-trauma fracture within the previous 5 years, falls during the previous year, glucocorticoid use for more than 3 months, and menopause before age 45 years. Fracture sites were recorded as hip, spine, wrist/shoulder/pelvis, or other, with fractures of the fingers and toes excluded from the other-site category. The questionnaire identified fractures as low trauma but did not collect a separate description of the injury mechanism. Fall frequency was categorized as none, 1 to 3, or 4 or more falls during the previous year. The menopause-before-age-45 item was displayed to women aged 45 to 64 years, with response options of yes, no, and a preselected "not yet menopausal" option. The stored default responses were classified separately from explicit yes/no responses in the analysis. Selected clinical items reflected factors

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incorporated in Thai Osteoporosis Foundation (TOPF) guidance [2].

Lifestyle-related items included current smoking, alcohol intake of more than 3 drinks per day, caffeine intake of more than 4 cups per day, weight-bearing exercise frequency, balance exercise, calcium intake frequency, and vitamin D exposure. Weight-bearing exercise was categorized as less than once per week, 1 to 2 times per week, or at least 3 times per week. Calcium intake was categorized as less often, 2 to 3 times per week, or almost daily. Vitamin D exposure was recorded as regular supplementation, regular sun exposure, or predominantly indoor living. The complete questionnaire, response options, and analytic definitions are provided in Table S1 in Multimedia Appendix 4.

App-Generated Bone Health Score and Scoring Algorithm

After completion, the app generated a Bone Health Score, a predefined user-facing score category, personalized recommendations, and a DXA-consideration prompt. The Bone Health Score was calculated using a rule-based weighted algorithm initialized at 100 points, with additions or deductions according to responses to selected clinical and lifestyle items. The scoring weights and category thresholds were predefined app-design parameters rather than thresholds derived from outcome-based statistical modeling. The complete response-to-point mapping is provided in Table S2 in Multimedia Appendix 4. The deployed questionnaire and scoring rules were reconstructed from archived app source files corresponding to the October 2025 to December 2025 study period.

For the questionnaire version deployed during the study period, the rendered user-entered items produced a theoretical score range of −15 to 140. Two additional fields present in the app code, disease count and treatment status, were not rendered as questionnaire items in the deployed version and therefore did not represent user-entered information in this analysis. Scores were grouped into 4 predefined app categories: “excellent” (>125), “good” (95-125), “needs improvement” (70-94), and “high risk” (<70). These labels are reported as user-facing app categories rather than clinical risk strata. The results interface displayed the numerical Bone Health Score without an explicit maximum. A fixed value of 150 was used to scale the circular progress indicator and as the upper limit of the score-history chart, rather than representing the theoretical maximum obtainable from the deployed questionnaire.

App-Generated DXA-Consideration Prompt and Logic

The app also generated a rule-based prompt suggesting consideration of bone mineral density measurement by DXA, informed by selected indications in the Thai Osteoporosis Foundation Clinical Practice Guideline [2]. The deployed algorithm used age thresholds of 65 years for women and 70 years for men. For assessments at age greater than 50 years and below the sex-specific age thresholds, the prompt could also be triggered by one or more captured criteria other than age: self-reported low-trauma fracture within the previous 5 years, BMI <20 kg/m², parental hip fracture, glucocorticoid use for more than 3 months, or menopause before age 45 years.

The implemented logic incorporated selected TOPF indications, with differences in age restrictions and the scope of captured clinical information. A comparison of the deployed rules with the corresponding TOPF indications is provided in Table S6 in Multimedia Appendix 4. Two sensitivity analyses were performed to evaluate the app-generated DXA-consideration prompt frequency. The first treated default/not-applicable early-menopause responses as unknown and excluded these assessments from the analysis, whereas the second removed the additional age >50 years restriction for explicitly reported early menopause. The prompt was analyzed as a guideline-informed app output, without determining formal TOPF eligibility. Assessments without recorded sex were excluded from the sex-specific DXA-prompt analyses.

Unit of Analysis and Repeat Assessments

The primary unit of analysis was the completed assessment. Because the app did not authenticate users and self-chosen nicknames could be reused, submissions could not be assigned to verified unique individuals. IP addresses were unavailable in the study dataset and were not used for identifying repeat submissions. All eligible completed assessments were retained in the primary analysis.

For repeat-assessment sensitivity analysis, nicknames were normalized by trimming leading and trailing whitespace and applying case-insensitive matching, without fuzzy spelling matches. Records sharing a normalized nickname were reviewed using age, sex, anthropometric characteristics, submission timestamps, and questionnaire response patterns. A deterministic rule identified probable repeat clusters based on matching normalized nicknames, identical recorded sex and age, and differences of no more than 0.5 kg in weight and 0.5 cm in height. The earliest assessment within each identified cluster was retained, while records with discordant characteristics were treated as separate assessments. The deterministic classification was compared with the structured manual review. The sensitivity dataset was used for descriptive analysis and was not considered a set of confirmed unique individuals.

Derived Variables and Exploratory Analyses

To describe the co-occurrence of selected unfavorable self-reported factors, an exploratory unweighted factor count was constructed from 8 questionnaire responses: weight-bearing exercise less than once per week, calcium intake less than 2 to 3 times per week, predominantly indoor vitamin D exposure, current smoking, alcohol intake of more than 3 drinks per day, glucocorticoid use for more than 3 months, caffeine intake of more than 4 cups per day, and no balance exercise. Each factor contributed 1 point when present. The count was used as a descriptive summary of co-occurring questionnaire characteristics rather than as a clinical risk score.

Sensitivity analyses recalculated the count after excluding glucocorticoid exposure, absence of balance exercise, and both factors simultaneously. The same distributions were additionally examined among assessments without an app-generated DXA-consideration prompt. Selected self-reported factors were

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summarized descriptively by age group (20-49, 50-64, 65-69, and ≥70 years) and by sex.

Sample Size

No formal a priori power calculation was performed because the study was designed as a descriptive and exploratory evaluation without an inferential primary end point. All eligible completed assessments generated during the defined study period were included in the analysis.

Statistical Analysis

Analyses were primarily descriptive. Continuous variables were summarized using mean and SD or median and IQR, as appropriate, with ranges reported where informative. Categorical variables were summarized as frequencies and percentages using the number of assessments with available data as the denominator. No weighting was applied for the convenience-sampling design.

App-generated outputs, subgroup summaries by age and sex, and unfavorable-factor counts were summarized descriptively. For the DXA-consideration prompt, sensitivity analyses excluded assessments with stored default/not-applicable early-menopause responses and separately removed the additional age >50 years restriction for explicitly reported early menopause, while retaining the other deployed rules. Sensitivity to probable repeat use was assessed by retaining the earliest assessment within each deterministically identified probable repeat cluster. Subgroup and sensitivity analyses were treated as descriptive summaries without hypothesis testing. Analyses were conducted in Python (version 3.12.12; Python Software Foundation), primarily using pandas (version 2.2.2; Pandas Development Team).

Data Handling and Privacy

Assessment records included submission timestamps, self-chosen nicknames, questionnaire responses, and app-generated outputs. Nicknames were stored as text fields and supported retrieval of previous Bone Health Scores and assessment dates for longitudinal comparison. No authenticated user account or identity verification was required, and records associated with reused nicknames were therefore considered linkable assessments. IP addresses were unavailable in the study dataset and were not used for linkage or repeat-assessment detection. The deployed information notice did not specify a data-retention period. For the present analysis, nicknames were used only to support the review of possible repeat assessments and were excluded from reported study outputs. Results are presented in aggregate form. Infrastructure-level encryption, access-control configurations, and device-level logging could not be independently verified retrospectively by the study team. Documentation sufficient to determine whether a formal institutional IT/security review occurred or whether any nickname-collision access incidents were recorded was not available for this retrospective analysis; the absence of identified incident records should not be interpreted as evidence that no incidents occurred. Any renewed public deployment would require authenticated history access and formal security review. The public app was subsequently taken offline.

Ethical Considerations

The web app was initially deployed as a public-facing bone health self-assessment initiative. Before beginning the assessment, users were shown an information notice describing the purpose of the tool, the voluntary nature of use, and the collection of questionnaire data for score generation, individualized recommendations, and aggregate analysis to support service improvement. Users proceeded by selecting an "accept and start" button. This study was a subsequent retrospective analysis of existing assessment records generated during this deployment. The retrospective study protocol was reviewed and approved by the Human Research Ethics Committee of Chulabhorn Royal Academy on May 8, 2026 (IRB 033/2569). The requirement for written informed consent for the retrospective analysis was waived by the ethics committee.

Results

Characteristics of Completed Assessments

The complete database export contained 304 submitted assessment records. Eight records were submitted outside the defined study period (October 9-December 20, 2025), leaving 296 records within the study period. After excluding 40 internal app-testing records, 256 eligible completed assessments were included in the primary analysis (Figure 1). The mean age was 51.9 (SD 14.0) years, and 195/256 (76.2%) assessments recorded female sex. Recorded ages ranged from 20 to 90 years, weights from 34 to 162 kg, heights from 143 to 187 cm, and calculated BMI from 15.4 to 70.3 kg/m². The median BMI was 22.3 kg/m² (IQR 20.2-25.3), with 59/256 (23%) having a BMI below 20 kg/m².

Self-reported parental hip fracture was recorded in 28/256 (10.9%) assessments. Thirteen assessments (5.1%) reported a low-trauma fracture within the previous 5 years, including 1 hip fracture, 1 spine fracture, 4 wrist/shoulder/pelvis fractures, and 7 fractures at other sites. Falls during the previous year were reported in 35/256 (13.7%) assessments, including 33 reporting 1 to 3 falls and 2 reporting 4 or more falls. Glucocorticoid use for more than 3 months was reported in 10/256 (3.9%) assessments. Among 98 assessments from women aged 45 to 64 years, 25 (25.5%) recorded menopause before age 45 years, 45 (45.9%) recorded no, and 28 (28.6%) retained the default/not-applicable response.

Several lifestyle-related patterns were common. Weight-bearing exercise less than once per week was reported in 115/256 (44.9%) assessments, and 197/256 (77%) reported no balance exercise. Calcium intake less often than 2 to 3 times per week was reported in 78/256 (30.5%), while 99/256 (38.7%) reported predominantly indoor vitamin D exposure. Current smoking, alcohol intake above 3 drinks per day, and caffeine intake above 4 cups per day were reported in 4/256 (1.6%), 1/256 (0.4%), and 16/256 (6.2%) of assessments, respectively. Full demographic, clinical, and lifestyle-related characteristics are presented in Table 1.

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Table 1. Characteristics and self-reported bone health–related factors in completed assessments (N=256)[a].

Characteristic	Value
Demographic and anthropometric characteristics	
Age (years), mean (SD)	51.9 (14.0)
Sex, n/N (%)	
Female	195/256 (76.2)
Male	59/256 (23)
BMI	
Median (IQR)	22.3 (20.2-25.3)
<20 kg/m², n/N (%)	59/256 (23)
Health history, n/N (%)	
Parental hip fracture	28/256 (10.9)
Self-reported low-trauma fracture within previous 5 years, n/N (%)	
Any fracture	13/256 (5.1)
Hip	1/256 (0.4)
Spine	1/256 (0.4)
Wrist/shoulder/pelvis	4/256 (1.6)
Other site	7/256 (2.7)
Falls in previous year, n/N (%)	
None	221/256 (86.3)
1-3	33/256 (12.9)
≥4	2/256 (0.8)
Glucocorticoid use >3 months	10/256 (3.9)
Menopause before age 45 among women aged 45-64 years[b], n/N (%)	
Yes	25/98 (25.5)
No	45/98 (45.9)
Default/not applicable	28/98 (28.6)
Health behaviors, n/N (%)	
Current smoking	4/256 (1.6)
Alcohol intake >3 drinks/day	1/256 (0.4)
Caffeine intake >4 cups/day	16/256 (6.2)
Weight-bearing exercise frequency (times/wk), n/N (%)	
≥3	89/256 (34.8)
1-2	52/256 (20.3)
<1	115/256 (44.9)
No balance exercise	197/256 (77)
Calcium intake, n/N (%)	
Almost daily	101/256 (39.5)
2-3 times/wk	77/256 (30.1)
Less often	78/256 (30.5)
Vitamin D exposure, n/N (%)	
Regular supplement use	75/256 (29.3)
Regular sun exposure	82/256 (32)

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Characteristic	Value
Predominantly indoor	99/256 (38.7)

[a]Values are mean (SD), median (IQR), or n/N (%), as indicated. Sex was not recorded for 2 assessments.

[b]The preselected "not yet menopausal" response was not interpreted as a confirmed negative because active selection was not required.

App-Generated Outputs and DXA-Consideration Prompts

The median Bone Health Score was 110 (IQR 90-120), with an observed range of 55 to 140. According to the predefined user-facing app categories, 38/256 (14.8%) assessments were classified as "excellent," 137/256 (53.5%) as "good," 77/256 (30.1%) as "needs improvement," and 4/256 (1.6%) as "high risk." These categories represent app-defined labels rather than validated clinical risk strata.

The DXA-consideration logic was evaluable in 254 assessments with recorded sex. The prompt was triggered in 94/254 (37%) assessments. Among triggered prompts, 44/94 (46.8%) resulted from the sex-specific age threshold, while 50/94 (53.2%) occurred below the age threshold because at least one captured non-age criterion was present. Among these 50 assessments, the contributing criteria were menopause before age 45 years in 24 (48%), BMI below 20 kg/m² in 21 (42%), parental hip fracture in 15 (30%), self-reported low-trauma fracture within the previous 5 years in 7 (14%), and glucocorticoid use for more than 3 months in 4 (8%). These criteria were not mutually exclusive. Detailed app-generated outputs are shown in Table 2.

Table 2. App-generated score outputs and dual-energy X-ray absorptiometry (DXA) consideration prompts[a].

Characteristic	Value
App-defined Bone Health Score	
Median (IQR)	110 (90-120)
Range	55-140
Score category, n/N (%)	
Excellent (>125)	38/256 (14.8)
Good (95-125)	137/256 (53.5)
Needs improvement (70-94)	77/256 (30.1)
High risk (<70)	4/256 (1.6)
App-generated DXA-consideration prompt	
Prompt status, n/N (%)	
Triggered	94/254 (37)
Not triggered	160/254 (63)
Basis for triggered prompt, n/N (%)	
Sex-specific age threshold	44/94 (46.8)
Below age threshold with ≥1 captured nonage criterion	50/94 (53.2)
Captured nonage criteria among below-age-threshold triggered prompts, n/N (%)	
Menopause before age 45	24/50 (48)
BMI <20 kg/m²	21/50 (42)
Parental hip fracture	15/50 (30)
Low-trauma fracture within previous 5 years	7/50 (14)
Glucocorticoid use >3 months	4/50 (8)

[a]Score categories are predefined user-facing app labels and have not been validated as clinical risk categories. The DXA-consideration prompt was evaluable in 254 assessments with recorded sex; 2 assessments were not evaluable because sex was not recorded. The prompt reflects the deployed guideline-informed app logic and does not represent formal Thai Osteoporosis Foundation eligibility or a clinical recommendation. Criteria other than age are not mutually exclusive.

In the complete-case sensitivity analyses, excluding 28 assessments with default/not-applicable early-menopause responses from the 254 assessments with recorded sex left 226 evaluable assessments, of which 93 triggered the DXA-consideration prompt (93/226, 41.2%). The higher percentage reflected the smaller denominator in this missing-data sensitivity analysis rather than an increase in the number of DXA-consideration prompts. Removing the additional age >50

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years restriction for explicitly reported early menopause resulted in 95/254 (37.4%) assessments triggering the prompt. A comparison of the deployed app logic with TOPF indications and the sensitivity analyses is provided in Table S6 in Multimedia Appendix 4.

Exploratory Descriptive Analyses

The exploratory 8-factor unfavorable self-reported factor count had a median of 2 (IQR 1-3) factors. Overall, 151/256 (59%) assessments had at least 2 factors and 97/256 (37.9%) had at least 3. The distribution was sensitive to the composition of the count. After exclusion of glucocorticoid exposure, 147/256 (57.4%) retained at least 2 factors. Excluding absence of balance exercise reduced this proportion to 98/256 (38.3%), while excluding both glucocorticoid exposure and absence of balance exercise resulted in 97/256 (37.9%) with at least 2 factors.

Selected questionnaire factors were also summarized descriptively by age group and sex in Table S3 in Multimedia Appendix 4. These subgroup summaries were exploratory and were presented without hypothesis testing or *P* values.

Among the 160 assessments with recorded sex that did not trigger the app-generated DXA-consideration prompt, 106/160 (66.2%) had at least 2 factors under the original 8-factor definition. This decreased to 71/160 (44.4%) when both glucocorticoid exposure and absence of balance exercise were excluded, illustrating the sensitivity of the descriptive count to its component definition. Full distributions under the alternative factor-count definitions are provided in Table S4 in Multimedia Appendix 4.

Repeat-Assessment Sensitivity Analysis

Eighteen repeated-nickname groups comprising 44 assessments were identified, including 15 groups with 2 assessments each and one group each with 3, 4, and 7 assessments. The deterministic matching rule identified 8 probable repeat clusters comprising 21 assessments, consistent with the earlier manual review. Retaining the earliest assessment within each cluster excluded 13 subsequent submissions and yielded a sensitivity dataset of 243 assessments. Because formal identity verification was not performed, this dataset was not interpreted as representing confirmed unique individuals.

Descriptive estimates were similar to those in the primary dataset. The proportion with an app-defined score below 95 changed from 31.6% in the primary analysis to 32.5% in the sensitivity dataset. The DXA-consideration prompt was triggered in 37% and 37.8%, respectively, while the proportions with at least 2 unfavorable factors were 59% and 60.9%. Across the selected measures evaluated, absolute differences between the primary and sensitivity analyses were small. Detailed comparisons between the primary and repeat-assessment sensitivity datasets are provided in Table S5 in Multimedia Appendix 4.

Discussion

Principal Findings

This study provides a real-world description of what a public-facing bone health self-assessment tool captured during routine deployment and how the collected information translated into app-generated outputs. The completed assessments represented a predominantly middle-aged and female user profile and contained a broad range of self-reported clinical and lifestyle-related characteristics. A key finding was the substantial contribution of non-age clinical factors to the DXA-consideration prompt. Although 37% of evaluable assessments generated a prompt, more than half of these occurred in assessments below the sex-specific age threshold because at least one captured non-age criterion was present. This suggests that the self-assessment process captured bone-health information that extended beyond demographic characteristics and contributed directly to the rule-based output. Co-occurring unfavorable self-reported factors were also common, although their frequency depended substantially on how the exploratory factor count was defined. Finally, the principal descriptive estimates changed only modestly in the repeat-assessment sensitivity analysis.

The predominantly female, middle-aged profile of completed assessments may reflect an intersection between the clinical salience of bone health and selection into digital engagement. Osteoporosis prevention becomes increasingly relevant to women around the menopausal transition and later life [1,2], while women are also prominently represented in osteoporosis-focused digital health studies [8]. At the same time, voluntary use of a web-based tool is unlikely to reflect disease relevance alone. Online health-information seeking has been associated with younger age, social media use, and higher educational attainment [14], and Thai data indicate substantially lower eHealth literacy among adults aged 60 years or older than among younger adults [15]. A broader review of digital health promotion in adults aged 50 years and older similarly found that study users were predominantly female and tended to have higher socioeconomic and digital competence profiles [16]. These observations suggest that the mean age of 51.9 (SD 14) years in our deployment may reflect a stage at which bone-health concerns are becoming more personally relevant while engagement with digital health may remain more feasible than at older ages. The dissemination channels may also have contributed to this pattern. Facebook-based recruitment has successfully engaged large numbers of women aged 45 years or older in bone-health research, although such recruitment also produced sociodemographic differences from the underlying population [17]. Finally, the frequency of unfavorable self-reported factors may partly reflect self-selection by individuals for whom bone health or related behaviors were already salient, a phenomenon described in other voluntary online self-assessment settings [18]. Thus, the observed profile is best interpreted as the characteristics represented among completed assessments in this self-selected deployment rather than as a population distribution of bone-health risk.

The app occupies a distinct role within the broader digital osteoporosis landscape. Existing digital approaches to osteoporosis span education, lifestyle support, self-management, clinical decision support, and patient-facing apps [8,9]. Digital osteoporosis tools have served different functions. Some provide formal personalized risk estimation using population-based and registry data [19], whereas others focus on self-management,

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medication management, usability, and follow-up among patients already engaged with clinical care [10,11,20]. In contrast, the Bone Health Score app was designed as a low-barrier, public-facing entry point that could be used independently outside a clinical encounter. A brief set of self-reported demographic, clinical, and lifestyle-related information was converted into immediate personalized feedback, behavioral recommendations, and a guideline-informed DXA-consideration prompt. This design is consistent with research on consumer-facing self-assessment tools in which users expressed a preference for tools that were quick and easy to use and provided personalized results [21]. Population-level web-based assessment tools in other health domains have also incorporated guideline-based questionnaire logic and evaluated their classifications against corresponding guideline criteria [22]. The intended role of the present app was to translate selected bone-health concepts into a simple self-assessment experience that could prompt users to reflect on modifiable behaviors and consider whether further evaluation might be appropriate. The finding that more than half of triggered DXA prompts occurred below the sex-specific age threshold illustrates how selected criteria other than age were incorporated into the app's rule-based assessment workflow.

The practical value of this deployment model lies in using self-assessment as an entry point that connects individualized bone-health information with actionable next steps. Data generated during routine use can also inform further development by showing which self-reported factors are commonly encountered, how app-generated outputs are distributed, and where additional guidance may be most useful. Experience with public-facing preventive health tools in other domains shows that these platforms can attract real-world use and support engagement with personalized recommendations [23]. In a national web-based cardiovascular risk tool, follow-up respondents also reported lifestyle changes and subsequent clinical checks after receiving personalized feedback [24]. These findings suggest that personalized feedback can provide a foundation for preventive engagement, particularly when users are given clear guidance on what to do with the information they receive. Evidence from digital risk-communication interventions further indicates that feedback may be more useful when combined with additional behavior-change support and opportunities for subsequent action [25]. For public-facing self-assessment tools, the next stage of development could prioritize actionable guidance on modifiable behaviors and clearer pathways to clinical evaluation when indicated. An iterative approach informed by acceptability, feasibility, adoption, and user feedback could guide further refinement [26].

This study has several strengths, including evaluation of a functioning public-facing tool under routine deployment conditions, detailed characterization of the self-reported information captured during use, transparent reporting of rule-based outputs, and sensitivity analysis addressing probable repeat assessments. The analysis also emphasized individual questionnaire factors and app-generated outputs rather than relying solely on the composite Bone Health Score. Several limitations should be considered. Use of the app was voluntary and dissemination occurred through hospital-linked social media and outpatient QR codes, producing a self-selected convenience sample whose characteristics may differ from those of the broader Thai population. Because of the cross-sectional design, temporal and causal relationships cannot be established, and the exploratory subgroup and sensitivity analyses should be interpreted as descriptive and hypothesis-generating. Clinical and lifestyle-related information was self-reported and not independently verified; recall or classification error may have resulted in either underreporting or overreporting of individual factors, while socially sensitive behaviors such as smoking and alcohol intake may have been underreported. The primary unit of analysis was a completed assessment rather than a verified unique individual because formal identity authentication was not used. Although estimates were similar in the repeat-assessment sensitivity analysis, some uncertainty regarding repeated use remains. Nickname-based history retrieval without authentication also posed a potential risk of unintended access to another user's prior score history. Website visitor counts, assessment initiations, and incomplete assessments were unavailable, limiting evaluation of reach, uptake, and completion patterns. Incomplete cross-step validation also allowed some submitted records to contain missing responses.

Available fracture information did not permit detailed confirmation of mechanism or temporality. Information on previous DXA testing, osteoporosis diagnosis, treatment history, and prior clinical evaluation was also unavailable, limiting interpretation of whether some users had previously unrecognized clinical risk. The Bone Health Score and its category thresholds were developed as user-facing outputs and have not undergone clinical validation. The circular score indicator was scaled to 150 rather than the maximum obtainable score of 140, although no numerical maximum was explicitly displayed to users. The implications of this graphical presentation for user interpretation were not evaluated. The percentile display was not explicitly identified to users as nonnormative and might have been mistaken for a population-based ranking. The unfavorable-factor count was exploratory and sensitive to its component definition. The DXA-consideration logic similarly incorporated selected guideline-informed factors available within the questionnaire and does not constitute formal guideline eligibility assessment. Because several TOPF indications were not captured and the deployed logic imposed additional age restrictions, the app may underidentify some guideline-indicated users and should not be interpreted as a surrogate for formal TOPF screening eligibility. The preselected early-menopause response introduced uncertainty in interpreting stored default values, and the deployed algorithm applied an additional age >50 years restriction to non-age DXA criteria. Sensitivity analyses examined these implementation choices, but full agreement with TOPF indications could not be established. Finally, usability, comprehension, changes in bone-health knowledge or behavior, subsequent care seeking, DXA completion, and clinical outcomes were outside the scope of this deployment study. Evaluating these outcomes will be important for determining the broader public health value of this type of self-assessment approach.

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These implementation limitations highlight several priorities for future app design. Clinically relevant questionnaire items, particularly those influencing DXA-consideration prompts, should require active responses or provide an explicit option for uncertain answers, supported by stronger input validation. The DXA-consideration logic should be reviewed against applicable clinical guidelines while maintaining a clear distinction between informational prompts and formal clinical recommendations. Score categories and percentile displays should communicate their interpretive limitations more clearly, and graphical score scales should be aligned with the attainable score range. Access to previous assessment scores should use secure, user-specific mechanisms rather than nickname matching alone. Privacy-conscious tracking of assessment initiation and completion could also support a more comprehensive evaluation of real-world engagement.

Conclusions

In this real-world deployment study, a public-facing web-based bone health self-assessment tool captured structured demographic, clinical, and lifestyle-related information during routine use and translated these data into immediate rule-based feedback. The completed assessments represented a predominantly middle-aged and female user profile, while non-age clinical factors contributed substantially to app-generated DXA-consideration prompts. The main descriptive estimates changed only modestly after excluding later assessments within high-probability repeat clusters. These findings describe the use of a low-barrier self-assessment format to deliver individualized rule-based bone health information during routine public deployment. Further prospective evaluation of usability, comprehension, behavior change, clinical follow-up, and linkage with objective assessment is needed to determine the broader public health role of this approach.

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Data Availability

The deidentified analytic dataset generated or analyzed during this study is not publicly available because it contains health-related assessment data derived from linkable records and has not been approved for unrestricted public deposition. Deidentified data may be available from the corresponding author on reasonable request, subject to approval under relevant institutional ethics and data governance requirements. The app scoring algorithm, DXA-consideration rules, and a consolidated Python script for reproducing the descriptive and sensitivity analyses are publicly available in the Bone Health Score GitHub repository (version 1.0.0) [27]. The repository includes the archived app calculation module, stand-alone scoring and DXA-prompt implementations, supporting documentation, and synthetic tests. No individual-level assessment data are included in the public repository.

Generative AI Use

During the preparation of this manuscript, the authors used Gemini (Google LLC) solely for language editing and improvement of English expression. All AI-assisted outputs were critically reviewed and revised by the authors, who take full responsibility for the accuracy, originality, integrity, and final content of the manuscript.

Authors' Contributions

RS contributed to the study conception and design, development of the Bone Health Score web app, methodology development, formal analysis, and original draft preparation. TR contributed to data acquisition, data curation, and quality assurance. NL contributed to interpretation of the data from a public health perspective and critical revision of the manuscript. NC contributed to study supervision, interpretation of the findings, and critical revision of the manuscript for important intellectual content, and served as the corresponding author. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

STROBE checklist for reporting the descriptive cross-sectional study.
[DOCX File , 38 KB-Multimedia Appendix 1]

Multimedia Appendix 2

CHERRIES checklist.

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[DOCX File , 33 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Representative screenshots of the Bone Health Score web app with English translations.
[DOCX File , 360 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Questionnaire items, scoring algorithm, exploratory analyses, sensitivity analyses, and dual-energy x-ray absorptiometry consideration logic.
[DOCX File , 47 KB-Multimedia Appendix 4]

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Abbreviations

CHERRIES: Checklist for Reporting Results of Internet E-Surveys
DXA: dual-energy X-ray absorptiometry
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology
TOPF: Thai Osteoporosis Foundation

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