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Review

The Role of Artificial Intelligence in Osteoporosis Risk Assessment in Type 2 Diabetes Mellitus: Pharmacological Dimensions and Personalized Therapy Perspectives

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Abstract

Skeletal fragility in type 2 diabetes mellitus (T2DM) is clinically important because fracture risk may remain elevated even when bone mineral density (BMD) is normal or increased. This discrepancy complicates screening, particularly when conventional fracture-risk prediction tools do not account for diabetes-specific factors, propensity to fall, or measures of bone quality. Glucose-lowering therapy may also affect skeletal outcomes, with effects that vary by drug class, while methods for using artificial intelligence (AI) to predict individual risk are advancing rapidly.

Objective: To summarize the evidence on fracture risk in adults with T2DM, the limitations of current risk-assessment tools, the effects of glucose-lowering therapy on skeletal outcomes, and the potential role of AI in personalized fracture prevention.

Methods. The search covered four predefined thematic areas: "diabetes and osteoporosis or fractures," "traditional fracture-risk assessment and trabecular bone score," "glucose-lowering therapy and skeletal outcomes," and "artificial intelligence/machine learning and fracture prediction." The main synthesis covered publications from 2020 to 2026. Twenty records from a selected, bibliographically verified reference set were reviewed; 19 were included in the qualitative analysis. These figures do not represent the full volume of the initial database search results. One landmark earlier cohort study was used for contextual discussion only.

Results. Current evidence confirms an increased incidence of fractures in T2DM and indicates that BMD and standard calculated risk estimates may not fully capture skeletal vulnerability. The most consistent adverse skeletal signal has been observed with thiazolidinediones. Findings for incretin-based therapies are generally neutral or favorable, although they vary according to treatment duration and study design. AI models have demonstrated promising discriminatory performance in certain populations; however, heterogeneity in outcome definitions and limited external validation do not yet support claims of universal superiority over conventional tools.

Conclusion. Fracture prevention in T2DM should be based on an integrated assessment of skeletal, metabolic, and fall-related factors. Clinical implementation of AI requires transparent reporting, calibration, and external validation.

Keywords: type 2 diabetes mellitus, osteoporosis, artificial intelligence, machine learning, personalized medicine, fracture risk.

1. Introduction

In adults with type 2 diabetes mellitus (T2DM), a reassuring DXA result does not always imply a low probability of fragility fracture. Bone mineral density (BMD) may be maintained while material properties and trabecular structure deteriorate. Long-standing hyperglycaemia, reduced bone turnover, diabetic microvascular complications and impaired balance contribute through different pathways [1–3]. This distinction matters at the outpatient visit: skeletal assessment should not end when the T-score falls outside the osteoporotic range.

The discrepancy between measured BMD and observed fractures is also a limitation of risk estimation. FRAX provides a standardized 10-year probability, but T2DM is not entered as a separate clinical variable. Clinicians should therefore interpret the estimate alongside diabetes duration, prior low-trauma fractures and fall susceptibility [6,7]. Trabecular bone score (TBS) provides complementary information about lumbar trabecular texture; it neither diagnoses fracture risk on its own nor replaces DXA [8,9].

Medication history adds another layer of clinical interpretation. Glucose-lowering classes differ in their associations with fractures, and apparent effects are sensitive to exposure time, comparator treatment and study design [11–15,22]. A history of hypoglycaemia is also relevant to falls. These considerations should be weighed against glycaemic, cardiovascular and renal indications rather than used as a stand-alone basis for changing treatment.

Prediction algorithms may integrate clinical, laboratory and functional variables that conventional calculators represent only partially. However, a model that performs well in a development sample may be poorly calibrated in another clinic. For AI-based fracture prediction, the clinically meaningful question is whether it changes identification and management of high-risk patients after independent validation [16–19].

This review examines evidence on four closely related decisions in T2DM care: recognizing diabetic skeletal fragility; interpreting FRAX, DXA and TBS; accounting for drug-related skeletal effects; and assessing the readiness of AI prediction models for outpatient use. The emphasis is on what the evidence supports in practice and where uncertainty remains.

2. Materials and methods

Review design

We undertook a structured, qualitative review of a curated evidence register. The available documentation does not contain a complete reproducible database yield or independent duplicate-screening record. Accordingly, this manuscript is not described as a PRISMA-compliant systematic review, and the selection summary must not be interpreted as a conventional PRISMA flow diagram.

Information source and search strategy

A structured search of PubMed-indexed literature was completed on 1 October 2026. The search was organized into four prespecified thematic blocks: “T2DM with osteoporosis or fracture”, “T2DM with FRAX, TBS or other fracture-risk assessment”, “T2DM with antidiabetic therapy and skeletal outcomes”, and “T2DM with AI/machine learning for osteoporosis or fracture prediction”. Search terms combined controlled concepts and free-text keywords with Boolean operators. Reference lists of relevant reviews were used to identify potentially missed records, after which every candidate citation was checked against a PMID and/or DOI before inclusion in the evidence register.

Eligibility criteria

Publications were considered eligible when they addressed adults with T2DM, or provided a separable T2DM subgroup, and reported outcomes related to fragility fracture, osteoporosis, BMD or bone quality, fracture-risk estimation, falls relevant to fracture risk, or predictive modelling. The main evidence window was 2020-2026. Primary research, systematic reviews, meta-analyses and clinically relevant reviews were eligible when methods and outcomes were sufficiently described for interpretation.

Records were excluded when they concerned type 1 diabetes alone, did not provide diabetes-specific results, described AI applications unrelated to bone, fracture or fall outcomes, or lacked sufficient methodological detail. Publications predating 2020 were not included in the formal synthesis, although landmark evidence could be cited separately when needed to explain the historical development of a risk-assessment issue.

Study selection and data extraction

The curated register contained 20 unique bibliographic records. Nineteen publications dated 2020–2026 were included in the thematic synthesis. One study published in 2012 was cited to explain the historical recognition of FRAX underestimation in diabetes, but was not counted among the 19 recent publications. The initial number of PubMed hits and duplicates removed cannot be reconstructed from the available register (Figure 1).

Risk-of-bias and evidence interpretation

The evidence set included several study designs for which a single appraisal tool would not be

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appropriate. No formal study-by-study risk-of-bias ratings are provided in the present manuscript; methodological limitations were considered narratively by study design. Particular attention was paid to sample size, representativeness, outcome definition, external validation, heterogeneity in pooled analyses, and whether reported predictive performance reflected internal or external testing.

Data synthesis

Findings were grouped into four domains: diabetic skeletal fragility and fracture epidemiology; conventional risk assessment and bone-quality measures; pharmacological influences on skeletal outcomes; and AI/ML-based prediction. Numerical results were reported only when they could be traced directly to a verified source. Because the underlying studies differed markedly in population, outcome definition and analytic method, no additional pooled effect estimate was calculated.

Evidence-register selection. Verified curated records (n=20) → Earlier contextual publication from 2012 (n=1) → Publications synthesized qualitatively from 2020–2026 (n=19). Original database hits, duplicates and full-text exclusion counts: not available.

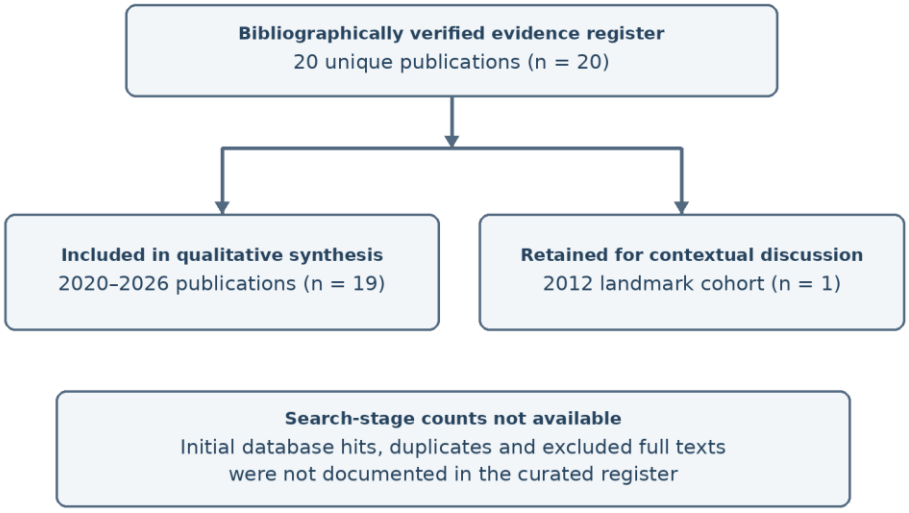


Figure 1 - Selection summary for the curated, bibliographically verified evidence register (20 records considered; 19 included in qualitative synthesis; one 2012 study retained for contextual discussion). This is not a PRISMA 2020 database-search flow diagram because identification and deduplication counts are unavailable

3. Results

Study selection and characteristics

The curated and bibliographically checked register comprised 20 unique publications; the number of records initially retrieved and removed as duplicates was not available in the present report. One cohort study published in 2012 was outside the predefined 2020-2026 window and was therefore not included in the qualitative synthesis, although it was retained as a contextual landmark citation. Nineteen publications met the criteria for qualitative synthesis. The included evidence consisted of 16 reviews or meta-analyses and three primary studies, spanning epidemiology, risk assessment, bone quality, pharmacotherapy and predictive modelling (Table 1).

Fracture risk and diabetic bone fragility

The clearest contemporary estimate came from a 2026 meta-analysis of 22 cohort studies comprising 13,074,868 participants.

T2DM was associated with a higher overall fracture risk (HR 1.25, 95% CI 1.20-1.31), with a stronger association reported for lower-limb fractures (HR 1.43, 95% CI 1.30-1.57) [5]. These data reinforce that the skeletal consequences of T2DM are clinically meaningful at a population level and extend beyond changes in BMD alone.

The clinical implication is not simply that BMD is an imperfect marker. A normal or elevated measurement in a patient with T2DM needs to be interpreted together with a prior fragility fracture, neuropathy, visual impairment and the likelihood of falling. The literature supports additional assessment where these features coexist, but does not establish a single universally valid diabetes-specific threshold [1–3].

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Table 1 - Characteristics of the 19 studies included in the structured evidence synthesis

ID	Year	Evidence domain	Study type	Population / sample	Main contribution
1	2023	AI / fracture prediction	Review	Patients with diabetes; review of conventional tools and AI	Reviews FRAX/QFracture/Garvan limitations and AI-based fracture prediction in diabetes.
2	2024	AI / fracture prediction	Original ML study	Patients with diabetes	Machine-learning study specifically addressing fracture-risk prediction in diabetes.
3	2025	AI / osteoporosis	Systematic review	13 studies; 24,489 patients	Systematic review comparing AI prediction performance with DXA and FRAX.
4	2022	Risk tools / FRAX	Review	People with diabetes	Summarizes FRAX, Garvan and QFracture; notes diabetes-specific limitations and possible adjustments.
5	2024	Diagnosis / BMD	Systematic review	Diabetes populations	Shows that fracture risk in T2D is not sufficiently explained by BMD/T-score alone.
6	2025	Epidemiology	Systematic review and meta-analysis	Observational studies	Reports higher osteoporosis and fracture risk in people with T2D.
7	2026	Epidemiology	Systematic review and meta-analysis	22 studies; 13,074,868 individuals	T2D associated with increased fracture risk, with site-specific differences.
8	2025	Risk tools / FRAX	Cohort / prediction performance	96,914 older adults with diabetes	FRAX showed acceptable discrimination overall but underestimated risk in important subgroups.
9	2025	TBS / bone quality	Systematic review and meta-analysis	27 studies; 16,354 subjects	T2D associated with lower TBS despite generally higher BMD; supports bone-quality assessment.
10	2023	TBS / bone quality	Narrative review	11 original studies; N=4,653 in sample-based analysis	Supports TBS as a potentially useful complement to BMD in T2D.
11	2022	Pharmacotherapy / fracture	Network meta-analysis	161 studies; 191,361 patients	Compares fracture risk across major antidiabetic drug classes; results differ by class.
12	2024	Pharmacotherapy / fracture	Systematic review and network meta-analysis	7 RCTs + 3 propensity-score NRSs	Long-term thiazolidinedione exposure increased fracture hazard, particularly in women; other classes did not show clear excess risk.
13	2024	Pharmacotherapy / BMD	Systematic review and meta-analysis	19 RCTs; 4,914 patients	Evaluates BMD and bone-turnover markers across antidiabetic therapies; evidence heterogeneous.
14	2025	Pharmacotherapy / GLP-1	Meta-analysis of RCTs	44 RCTs; 47,823 patients	Pooled analysis reported lower fracture risk with GLP-1 receptor agonists versus placebo/other therapies.
15	2025	Pharmacotherapy / fracture	Network meta-analysis	242 studies; 234,759 individuals	Recent comparative evidence on fracture outcomes and BMD across antidiabetic treatments.
16	2021	Pharmacotherapy / fracture	Systematic review and network meta-analysis	117 RCTs; 221,364 participants	Large network meta-analysis; effects varied across drugs and estimates were heterogeneous.
17	2022	Bone quality / microstructure	Narrative review	T2D bone fragility literature	Summarizes limitations of DXA/FRAX and newer approaches including TBS, HR-pQCT and biomarkers.

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Table 1 (Continuation) - Characteristics of the 19 studies included in the structured evidence synthesis

ID	Year	Evidence domain	Study type	Population / sample	Main contribution
18	2023	Risk tools / clinical practice	Cross-sectional / clinical assessment	Adults with T2D	Shows practical application of FRAX and a high burden of fracture-risk factors in T2D.
19	2021	Bone fragility overview	Narrative review	T2D	Clinical overview of diabetic skeletal fragility, medication effects, and limitations of FRAX/DXA.

FRAX, TBS and conventional risk assessment

FRAX, Garvan FRC and QFracture are used to estimate fracture probability, but their inputs and target populations differ. In T2DM, the omission of diabetes-specific features can affect calibration, especially in particular patient subgroups [6,7]. A calculated probability should therefore be treated as one element of clinical assessment, not an automatic referral or treatment decision.

TBS may partly address the gap between bone mass and bone quality. A 2025 systematic review and meta-analysis encompassing 27 studies and 16,354 participants found lower TBS values in people with T2DM despite the tendency toward higher BMD [8]. An updated review reached a similar conclusion and suggested that TBS can complement, rather than replace, standard densitometric assessment [9]. The value of TBS in routine care nevertheless depends on availability, standardized interpretation and evidence that its use changes clinical decisions.

Pharmacological dimensions

Six included evidence syntheses examined the skeletal effects of glucose-lowering treatment. Their conclusions were not uniform, largely because they differed in drug classes, comparators, duration of follow-up and chosen skeletal endpoints. A 2021 network meta-analysis of 117 randomized trials involving 221,364 participants found meaningful between-class variation in fracture outcomes [11]. A separate 2022 network meta-analysis of 161 studies and 191,361 patients likewise showed that fracture risk was not distributed evenly across treatment classes [12].

Longer exposure appears particularly relevant for thiazolidinediones. A 2024 one-stage network meta-analysis (seven randomized trials and three propensity-score-matched observational studies) reported an overall 42% higher fracture hazard with thiazolidinediones (95% credible interval, 3%–97%).

The reported hazard ratio after four years was 2.74 (95% credible interval, 1.53–4.80), with a stronger association among women (HR 2.19; 95% credible interval, 1.26–3.74). These estimates are study-specific and should not be generalized to every treatment setting [22]. By contrast, a 2024 systematic review of 19 randomized trials involving 4,914 patients found that effects on BMD and bone-turnover markers varied across therapies and were often limited by heterogeneity and short follow-up [13]. A larger 2025 network meta-analysis reached a similarly cautious conclusion, emphasizing that treatment comparisons should not be interpreted without regard to patient characteristics and exposure duration [15].

For GLP-1 receptor agonists, a meta-analysis published in 2025 of 44 randomized trials and 47,823 participants reported a pooled fracture risk ratio of 0.77 (95% CI 0.61-0.96) compared with placebo or other glucose-lowering treatments [14]. Although this suggests a potentially favorable association, fracture outcomes were not the primary endpoint of many contributing trials. The result is therefore more appropriately viewed as a supportive safety signal than as a basis for selecting therapy solely to prevent fractures (Table 2).

AI and machine-learning prediction

The reviewed AI literature addresses different prediction targets and uses datasets of unequal size and composition. This is important when interpreting apparently comparable AUC or accuracy values: a model predicting prevalent osteoporosis is not directly comparable with one predicting incident fracture. The 2023 review identified potential benefits of more flexible models but also limited independent validation [16].

In a diabetes-specific clinical ML study, feature selection was combined with several algorithms for fracture prediction. The Random Forest model achieved a reported predictive accuracy of 93.87% [18]. This finding demonstrates the technical potential of ML, but the result represents performance within the study setting and cannot by itself establish generalizability to other populations, clinical workflows or health systems.

A 2025 systematic review comparing AI-based fracture prediction with DXA and FRAX included 13 studies and 24,489 patients. Across the included AI studies, the mean reported AUC was approximately 0.93, with high sensitivity in several comparisons [17].

Because model architecture, population characteristics, outcome definitions and validation strategies differed substantially across studies, the pooled descriptive estimate should not be interpreted as a universal performance benchmark.

Table 2 - Selected verified quantitative findings relevant to clinical interpretation

Evidence	Population	Main estimate	Interpretation	Reference
T2DM and overall fracture risk	22 cohort studies; 13,074,868 participants	HR 1.25 (95% CI 1.20–1.31)	Fracture risk is higher in T2DM across multiple skeletal sites	[5]
Lower-limb fracture risk in T2DM	Same meta-analysis	HR 1.43 (95% CI 1.30–1.57)	Particularly relevant to hip/ankle/foot fracture prevention	[5]
GLP-1 receptor agonists and fracture	44 RCTs; 47,823 patients	RR 0.77 (95% CI 0.61–0.96)	Potential favorable signal; not sufficient alone to drive prescribing	[14]
AI fracture prediction systematic review	13 studies; 24,489 patients	Mean reported AUC approximately 0.93	Promising discrimination, but between-study heterogeneity limits direct comparison	[17]
Diabetes-specific ML fracture model	Clinical ML study	Random Forest predictive accuracy 93.87%	Strong internal performance; external validation remains necessary	[18]

Implications for personalized therapy

Risk assessment is most useful when it leads to a specific clinical action. For example, previous low-trauma fracture or recurrent falls may warrant further evaluation even when BMD is not markedly reduced. Peripheral neuropathy, visual disturbance, hypoglycaemic episodes and treatment history should be documented because they may influence both fracture probability and the feasibility of prevention.

A practical outpatient assessment may begin with fracture and fall history, proceed to medication and diabetes-complication review, and then incorporate established fracture-risk tools and DXA when clinically indicated. TBS can provide supplementary information where available. An AI-derived score should be introduced into this sequence only after local calibration, external validation and a clear plan for managing positive and negative results.

4. Discussion

Three issues emerge from the evidence. First, BMD alone can understate skeletal vulnerability in T2DM. Second, estimates of medication-associated risk differ across drug classes and study methods. Third, the apparent advantage of AI models is not yet equivalent to demonstrated clinical benefit. These issues are linked in practice, but they require different forms of evidence and should not be combined into a single performance claim.

The epidemiological evidence is now substantial. The 2026 meta-analysis involving more than 13 million participants demonstrates that the excess fracture risk associated with T2DM is not confined to a single skeletal site [5]. This finding supports routine attention to skeletal health in diabetes care, especially in patients whose risk is amplified by age, long disease duration, neuropathy or recurrent falls.

Risk estimation remains difficult because commonly used tools were developed for broad populations rather than the full diabetic phenotype. FRAX continues to provide a useful standardized comparator, yet its output should not be treated as self-sufficient in T2DM. TBS offers one way to capture information related to trabecular texture and may be particularly informative when BMD appears reassuring despite substantial clinical risk [8,9].

The medication findings require careful qualification. Increased fracture risk with prolonged thiazolidinedione exposure has support in comparative evidence, particularly among women [22]. For GLP-1 receptor agonists, pooled trial results are more reassuring, but fractures were often secondary or uncommon outcomes [14]. Neither pattern should be interpreted as a universal prescribing rule; duration, baseline risk, competing indications and certainty of evidence matter.

The performance of an AI tool should be judged against a clinically relevant comparator in the population where it will be used. Important measures include calibration, discrimination with uncertainty intervals, rates of missed high-risk patients and the consequences of additional referrals. Independent

validation is a prerequisite for claims that a model can improve care beyond the development setting.

In Kazakhstan, the existing country-specific FRAX model offers a defined comparator for outpatient research. A prospective evaluation could assess whether diabetes duration, complications and falls history improve risk stratification after accounting for FRAX. The same study would need to assess access to confirmatory DXA and completion of preventive care; otherwise, better prediction could leave the clinical pathway unchanged.

Strengths and limitations

The principal contribution of this review is its explicit separation of clinical, pharmacological and prediction-model evidence. Bibliographic identifiers were checked within the curated register, and numerical findings are discussed in the context of the corresponding study designs. This improves traceability, but is not equivalent to formal study-level appraisal.

Several limitations affect interpretation. The original search yield, duplicate counts and independent screening decisions were not available, and a formal risk-of-bias assessment was not completed for every included study. The evidence base combines primary research and reviews, so some populations may appear in more than one synthesis. Outcomes and prediction metrics are heterogeneous; consequently, we have not calculated a new pooled effect or made a quantitative claim of AI superiority.

5. Conclusion

Patients with T2DM may have clinically meaningful fracture susceptibility despite relatively preserved BMD. Assessment should combine prior fractures, falls, diabetes-related complications and medication exposure with validated clinical tools; TBS may complement DXA where available. The evidence concerning glucose-lowering therapy is heterogeneous, although prolonged thiazolidinedione use warrants particular attention to skeletal safety. AI models are promising research tools, but outpatient adoption should follow independent validation, calibration and evaluation of referral consequences. The immediate priority is a reliable clinical pathway that identifies patients who can benefit from assessment and prevention.

Conflict of Interest. Gulnara Zh. Sakhipova is the inventor and patent holder of Kazakhstan Utility Model Patent No. 11999, which is related to the subject matter of this review. The remaining authors declare no financial or non-financial conflicts of interest relevant to this manuscript.

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AI Declaration. Generative AI was used during manuscript preparation for language editing and text organization. All scientific statements, numerical results, references and interpretations were reviewed by the authors, who take full responsibility for the final manuscript. AI-generated output was not treated as scientific evidence and was not used in place of bibliographic verification.

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2-типті қант диабеті кезінде остеопороз қаупін бағалаудағы жасанды интеллектінің рөлі: Фармакологиялық аспектілер және дербестендірілген терапия

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Түйіндеме

2-типті қант диабеті (2-типті ҚД) кезіндегі сүйек осалдығының клиникалық маңызы зор, өйткені сүйек тінінің минералдық тығыздығы (СТМТ) қалыпты немесе жоғары болғанның өзінде сыну қаупі жоғары болып қалуы мүмкін. Аталған сәйкессіздік скрининг жүргізуді қиындатады, әсіресе дәстүрлі сыну қаупін болжау құралдары ҚД-іне тән факторларды, құлау бейімділігін және сүйек сапасының көрсеткіштерін ескермеген жағдайда. Қантты төмендететін емнің де әсері бар: дәрілік заттар кластарының сүйекке ықпалы әртүрлі. Сонымен қатар жеке сыну қаупін болжауға арналған жасанды интеллект (ЖИ) әдістері қарқынды дамып келеді.

Шолудың мақсаты: 2-типті ҚД бар ересектердегі сыну қаупі, оны бағалаудың қолданыстағы құралдарының шектеулері, қантты төмендететін емнің сүйекке әсері және сынудың дербестендірілген профилактикасындағы ЖИ-дің ықтимал рөлі туралы деректерді жинақтау.

Әдістері. Іздеу алдын ала белгіленген 4 тақырыптық блок бойынша жүргізілді: «қант диабеті және остеопороз немесе сынулар», «сыну қаупін дәстүрлі бағалау және трабекулалық сүйек индексі», «қантты төмендететін ем және сүйекке қатысты нәтижелер», сондай-ақ «жасанды интеллект/машиналық оқыту және сынуды болжау». Негізгі синтезге 2020–2026 жылдары жарияланған еңбектер енгізілді. Іріктелген әрі библиографиялық тексеруден өткен дереккөздер тізіліміндегі 20 жазба қарастырылып, оның 19-ы сапалық талдауға енгізілді. Аталған көрсеткіштер іздеу базасындағы бастапқы нәтижелердің толық көлемін қамтымайды. 2020 жылдан ертерек жарияланған бір маңызды когорталық зерттеу тек контекстік талқылау үшін пайдаланылды.

Нәтижелері. Қазіргі деректер 2-типті ҚД кезінде сыну жиілігінің жоғары екенін растайды және СТМТ мен стандартты есептік көрсеткіштер сүйек осалдығын толық сипаттамауы мүмкін екенін көрсетеді. Сүйекке ең тұрақты жағымсыз әсер тиазолидиндиондар үшін анықталған. Инкретиндік емге қатысты нәтижелер көбіне бейтарап немесе қолайлы болғанымен, ем ұзақтығына және зерттеу дизайнына байланысты өзгереді. Жекелеген популяциялардағы ЖИ модельдері сыну қаупін ажырату қабілеті тұрғысынан үміт күттіретін нәтижелер көрсетті. Алайда соңғы нүктелердің әркелкілігі мен сыртқы валидацияның жеткіліксіздігі олардың дәстүрлі құралдардан жалпыға бірдей артық екенін тұжырымдауға әзірше мүмкіндік бермейді.

Қорытынды. 2-типті ҚД кезінде сынудың алдын алу сүйекке, зат алмасуға және құлау қаупіне қатысты факторларды кешенді бағалауға негізделуі керек. ЖИ-ді клиникалық тәжірибеге енгізу үшін нәтижелерді ашық түрде баяндау, модельдерді калибрлеу және сыртқы валидациядан өткізу қажет.

Түйін сөздер: 2-типті қант диабеті, остеопороз, жасанды интеллект, машиналық оқыту, дербестендірілген медицина, сынық қаупі.

Роль искусственного интеллекта в оценке риска остеопороза при сахарном диабете 2 типа: Фармакологические аспекты и персонализированная терапия

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Резюме

Скелетная хрупкость при сахарном диабете 2 типа имеет важное клиническое значение, поскольку риск переломов может оставаться повышенным даже при сохраненной или увеличенной минеральной плотности костной ткани. Такое несоответствие усложняет скрининг, особенно когда традиционные инструменты прогнозирования переломов не учитывают специфические для сахарного диабета факторы, склонность к падениям и показатели качества кости. Дополнительное влияние оказывает сахароснижающая терапия, классы которой различаются по скелетным эффектам, а также быстрое развитие методов искусственного интеллекта для индивидуального прогнозирования риска.

Цель обзора: обобщение данных о риске переломов у взрослых с сахарным диабетом 2 типа, ограничениях существующих инструментов оценки, влиянии сахароснижающего лечения на костные исходы и возможной роли ИИ в персонализированной профилактике переломов.

Методы. Поиск выполнен по четырем заранее определенным тематическим блокам: “сахарный диабет и остеопороз или переломы”, “традиционная оценка риска переломов и трабекулярный костный индекс”, “сахароснижающая терапия и скелетные исходы” и “искусственный интеллект/машинное обучение и прогнозирование переломов”. Основной синтез охватывал публикации 2020–2026 годов. Рассмотрены 20 записей из отобранного библиографически проверенного реестра, из них 19 источников вошли в качественный анализ. Указанные показатели не отражают весь объем первоначальной выдачи поисковой базы, одна более ранняя знаковая когортная работа использована только для контекстного обсуждения.

Результаты. Современные данные подтверждают повышенную частоту переломов при сахарном диабете 2 типа и показывают, что минеральная плотность костной ткани и стандартные расчетные показатели могут неполно отражать скелетную уязвимость. Наиболее устойчивый неблагоприятный скелетный сигнал выявлен для тиазолидиндионов. Результаты по инкретиновой терапии чаще нейтральные или благоприятные, однако зависят от длительности лечения и дизайна исследований. Модели ИИ демонстрируют перспективную дискриминационную способность в отдельных выборках, но неоднородность конечных точек и недостаток внешней валидации пока не позволяют утверждать их универсальное превосходство над традиционными инструментами.

Выводы. Профилактика переломов при сахарном диабете 2 типа должна основываться на интегрированной оценке скелетных, метаболических и связанных с падениями факторов, а клиническое внедрение ИИ требует прозрачной отчетности, калибровки и внешней валидации.

Ключевые слова: сахарный диабет 2 типа, остеопороз, искусственный интеллект, машинное обучение, персонализированная медицина, риск переломов.

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