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REVIEW

Artificial Intelligence in Podiatric Practice: From Gait Analysis to Diabetic Foot Risk Prediction

Inteligencia artificial en la práctica podológica: del análisis de la marcha a la predicción del riesgo de pie diabético

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ABSTRACT

Artificial intelligence has expanded rapidly across podiatric care, from automated gait analysis to the prediction of diabetic foot complications. This narrative review synthesizes the evidence published between 2016 and 2025 on the applications, reported performance, and limitations of these tools. A documented search into five thematic axes: automated gait analysis and biomechanical assessment; diabetic foot risk prediction and ulcer assessment; diagnostic imaging and foot deformity classification; wearable sensing and remote monitoring; and validation, bias, and clinical translation. Deep learning reconstructs plantar pressure and joint kinetics from wearable signals and automates radiographic measurements of foot deformities. Prediction models for diabetic foot ulcers, amputation, and recurrence report areas under the curve between 0.89 and 0.97 in internal validation, although performance attenuates on external testing. Wearable insoles and sensor-enabled dressings extend monitoring beyond the clinic. Convergent evidence indicates that most models remain single-center proof-of-concept studies without prospective deployment, and that podiatrists favor supportive rather than autonomous roles for artificial intelligence. Future research should prioritize external validation, fairness, and implementation studies that link these tools to clinical outcomes.

Keywords: artificial intelligence; machine learning; podiatry; gait analysis; diabetic foot; risk assessment.

RESUMEN

La inteligencia artificial se ha expandido con rapidez en la atención podológica, desde el análisis automatizado de la marcha hasta la predicción de complicaciones del pie diabético. Esta revisión narrativa sintetiza sobre las aplicaciones, el rendimiento reportado y las limitaciones de estas herramientas. Una búsqueda documentada en Scopus, OpenAlex, PubMed y Crossref identificó estudios organizados en cinco ejes temáticos: análisis automatizado de la marcha y evaluación biomecánica; predicción del riesgo de pie diabético y valoración de úlceras; imagen diagnóstica y clasificación de deformidades del pie; sensores vestibles y monitorización remota; y validación, sesgo y traslación clínica. El aprendizaje profundo reconstruye la presión plantar y la cinética articular a partir de señales vestibles y automatiza las mediciones radiográficas de las deformidades del pie. Los modelos de predicción de úlceras de pie diabético, amputación y recurrencia reportan áreas bajo la curva entre 0,89 y 0,97 en la validación interna, aunque el rendimiento se atenúa en la prueba externa. Las plantillas instrumentadas y los apósitos con sensores extienden la monitorización más allá de la consulta. La evidencia convergente indica que la mayoría de los modelos siguen siendo pruebas de concepto unicéntricas sin despliegue prospectivo, y que los podólogos prefieren roles de apoyo antes que autónomos para la inteligencia artificial. La investigación futura debe priorizar la validación externa, la equidad y los estudios de implementación que vinculen estas herramientas con desenlaces clínicos.

Palabras clave: inteligencia artificial; aprendizaje automático; podología; análisis de la marcha; pie diabético; medición de riesgo.

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INTRODUCTION

Diabetic foot disease and disorders of gait and foot structure concentrate a large share of preventable disability in adult populations. A meta-analysis of the global epidemiology of diabetic foot ulceration reported a pooled prevalence of 6.3% (95% CI 5.4 to 7.3), with the highest regional estimate in North America at 13.0%.(1) Foot ulceration is the most common lower-extremity complication of diabetes, and recurrence after healing remains common even with structured prevention.(2) The scale of the problem is considerable: it has been estimated that a person with diabetes develops a foot ulcer every second and that at least half of these wounds become infected.(3) Gait impairment and fall risk extend this burden beyond diabetes to older adults, in whom foot-mounted inertial sensors have resolved distinct walking phenotypes with fall prevalence ranging from 27% to 68%.(4) For the podiatrist, the clinical workload spans repetitive measurement of angles and arch height, interpretation of plantar pressure and gait, and risk stratification of the diabetic foot, all of which are tasks that pattern recognition can support.

Artificial intelligence entered clinical medicine through risk assessment and image analysis, and its reach broadened substantially once deep learning matured in the early 2000s.(5) Machine learning differs from conventional statistical modeling in its emphasis on prediction rather than inference and in its capacity to learn directly from high-dimensional signals such as images and sensor time series.(6) In diabetes care, these methods have been proposed for screening and diagnostics, including cloud-based prediction from routine clinical variables such as glucose, body mass index, and age,(7) and reviews of artificial intelligence in diabetes describe gains in diagnostic accuracy alongside unresolved challenges in deployment.(8) The same techniques apply directly to the foot, where the signals of interest, plantar pressure, gait kinematics, wound photographs, and radiographs, are abundant and increasingly digitized, which makes podiatry well suited to clinical machine learning.

Within podiatry the literature is fragmented by task and by modality. Reviews have synthesized image-based diagnosis of diabetic foot ulcers,(9) thermography of the diabetic foot,(10) smart wearable technology for the diabetic foot,(11) digital health technologies for ulcer care,(12) and computational methods for chronic wounds.(13) Each of these addresses a single technique or condition, and none integrates the span from gait analysis to risk prediction or examines in one place the recurring problems of external validation, bias, and clinical translation. The result is that a clinician seeking an overview of what artificial intelligence can already do, and what it cannot yet be trusted to do, finds no single synthesis to consult. The most recent wave of studies, published in 2024 and 2025, has moved from single-center proof of concept toward multicenter prediction and portable measurement, which makes the present moment the point at which a critical synthesis of the state of the field is most useful to clinicians.

The objective of this review is to synthesize the evidence on the applications of artificial intelligence in podiatry published between 2016 and 2025 and to characterize their methodological strengths, limitations, and barriers to clinical translation. Specifically, the review describes the main approaches used in gait analysis and biomechanical assessment; examines the reported performance and clinical validity of models for diabetic foot risk prediction and ulcer assessment; identifies applications in diagnostic imaging, wound care, and remote monitoring; and characterizes the validation gaps and translation barriers that separate these tools from routine practice.

DEVELOPMENT

The synthesis included 65 studies distributed across five thematic axes (Table 1). The axes move along the clinical pathway, from the biomechanical signals of gait and plantar pressure to the prediction of diabetic foot outcomes, and close with the methodological conditions that determine whether any of these tools reaches practice.

Automated gait analysis and biomechanical assessment

Plantar pressure and forceplate recordings are the dominant data sources for automated foot and gait assessment, and deep learning is increasingly used to estimate kinetic quantities that previously required laboratory equipment. A dataset of high-resolution plantar pressures collected across footwear conditions and walking speeds illustrates the shift toward open, reusable resources for model development.(15) From single forceplate signals, a physics-informed deep network has been proposed to predict bilateral ground reaction forces and center of pressure, which reduces the need for patients to target separate plates during walking trials.(16) Similar objectives are pur-

sued from wearable inertial sensors: cross-modal learning can infer plantar pressure distribution, ground reaction force, and center of pressure from inertial measurement units,(17) and a hybrid convolutional recurrent network estimates dynamic plantar pressure distributions from wearable signals as a portable alternative to laboratory platforms.(18) Ankle joint moments, which require inverse dynamics modeling in a laboratory, have also been estimated from pressure insoles through a combination of genetic-algorithm sensor selection and deep forest regression (19) (Table 2).

Table 1. Synthesis of artificial intelligence applications in podiatry by thematic axis.

Axis	Core tasks	Key finding	Studies (n)
Gait analysis and biomechanics	Plantar pressure, ground reaction forces, joint kinetics, arch assessment	Deep learning reconstructs kinetics from wearable signals and automates arch assessment	11
Diabetic foot risk and ulcer assessment	Ulcer classification, amputation, recurrence, neuropathy prediction	High internal discrimination, attenuated on external validation	19
Diagnostic imaging and deformity classification	Radiographic angles, landmarks, arch type	Automated measurements comparable to expert reading	13
Wearable sensing and remote monitoring	Insoles, smart dressings, fall detection	Feasibility demonstrated, clinical effectiveness undefined	8
Validation, bias, and translation	External validation, fairness, explainability, language models	Scarce external validation; trust and bias unresolved	14

Note: The number of studies reflects the primary axis to which each study was assigned in the argument matrix.

Table 2. Representative models for automated gait and biomechanical assessment.

Study	Task	Data source	Approach
Physics-informed deep learning (16)	Bilateral GRF and CoP	Single forceplate	Physics-informed residual network
Motion2Press (17)	Plantar pressure, GRF, CoP	IMU	Cross-modal deep learning
Hybrid CNN-BiLSTM (18)	Dynamic plantar pressure	IMU	Convolutional recurrent network
Ankle moment estimation (19)	Ankle joint moment	Pressure insoles	Genetic algorithm plus deep forest
Multicenter segmentation (20)	Plantar pressure analysis	Pressure platforms	Machine learning segmentation
Arch index estimation (21)	Foot arch index	Plantar pressure	Deep learning system
Flatfoot detection insole (22)	Flatfoot screening	Triboelectric insoles	Self-powered sensing plus learning

Note: GRF = ground reaction force; CoP = center of pressure; IMU = inertial measurement unit.

A second line of work automates the analysis of plantar pressure images themselves. Conventional proportion-based segmentation of the foot into regions is limited for atypical foot structures, and machine learning segmentation trained across multicenter data has been advanced as a more robust alternative.(20) The same pressure images support arch assessment: a deep learning plantar pressure system estimates the foot arch index for static evaluation of flatfoot and high arch,(21) and a self-powered triboelectric insole detects flatfoot during gait.(22) These tools pursue the same objective: replacing subjective or time-consuming clinical measurement of the medial longitudinal arch with reproducible digital estimates.

Gait classification extends beyond kinetics to diagnostic support. Force sensors combined with machine learning have been used for severity classification in Parkinson disease,(23) and pressure-sensing insoles that capture center-of-pressure features during the timed up and go test distinguished Parkinson disease from controls using 144 features in a study of 77 participants.(24) A flexible triboelectric pressure array combined with deep learning provides a soft, self-powered gait detection system intended for continuous health assessment.(25) These systems resolve foot-specific kinetic, arch, and balance quantities with reported accuracy comparable to reference instruments, although none of them has been evaluated in routine podiatric practice. The convergence of the axis is technical maturity; the divergence is between laboratory equivalence and clinical deployment, and no study in this axis reported a prospective change in podiatric decision making.

A further convergence is methodological. The field is moving from proprietary, single-laboratory data toward shared resources and multicenter benchmarks, as the open plantar pressure dataset(15)and the multicenter segmentation work(20)illustrate. This trajectory matters for podiatry because arch and pressure reference values vary with footwear, walking speed, and population, and models trained on one laboratory's data inherit those confounders. The absence of agreed benchmark tasks remains a divergence that slows comparison across studies and prevents the field from stating, on common ground, which of the competing sensor and learning combinations is superior. In the podiatric workflow, the immediate beneficiaries of this axis are the measurement and screening steps of the examination, arch typing, pressure mapping, and gait screening, which currently consume examiner time and introduce between-observer variation that automated estimates could reduce.

Diabetic foot risk prediction and ulcer assessment

The largest body of work addresses the diabetic foot, where the clinical stakes are highest. Image-based deep learning models classify diabetic foot ulcers from photographs, and explainability frameworks are increasingly added to support clinical trust: a feature-explainability framework was proposed for ulcer identification,(26)and an explainable swin transformer model was developed for ulcer classification.(27)A systematic review of image-based diagnosis concluded that detection, segmentation, and classification are the three dominant tasks and that reported accuracies are high, while prospective clinical validation is scarce.(9)

Clinical prediction models built on routine variables target amputation, the most severe outcome. In 598 patients with diabetic foot ulcers, a gradient boosting machine using 17 selected features predicted major amputation with an area under the curve of 0.95 and accuracy of 0.94, with multidrug-resistant infection, C-reactive protein, and diabetes duration as the leading predictors.(28) A support vector machine trained on 149 patients reached an area under the curve of 0.89, and identified C-reactive protein and Wagner grade as independent predictors of amputation.(29) A larger model of 1,332 patients reported an internal area under the curve of 0.93 with XGBoost, which fell to 0.83 on external validation in a separate multicenter cohort, a pattern that illustrates the gap between internal and external performance.(30) A review of risk prediction models for the diabetic foot confirms this rapid growth and the same recurring limitation (31) (Table 3).

Table 3. Representative models for diabetic foot risk prediction and ulcer assessment.

Study	Outcome	Population	Model and key performance
Corneal nerve imaging (32)	Diabetic foot risk	471 participants	Deep learning plus HbA1c, AUC 0.94
Major amputation (28)	Amputation	598 patients	Gradient boosting, AUC 0.95
Multicenter prediction (33)	Incident diabetic foot	6,180 older adults	Logistic ensemble, AUC 0.94
Infection versus osteomyelitis (34)	Differential diagnosis	3,612 patients	LightGBM, external AUC 0.94
Amputation (30)	Lower-extremity amputation	1,332 patients	XGBoost, internal AUC 0.93, external 0.83
Recurrence (35)	Three-year recurrence	494 patients	XGBoost, AUROC 0.92
Amputation (29)	Amputation	149 patients	Support vector machine, AUC 0.89
Ulcer in arterial occlusion (36)	Incident ulcer	Diabetic patients with occlusion	Clinical model, AUC 0.96

Note: AUC = area under the curve; AUROC = area under the receiver operating characteristic curve.

Multicenter development represents a step toward generalizable prediction. A study of 6,180 older adults from 11 community hospitals combined deep and classical learning and reported a logistic regression ensemble with areas under the curve of 0.94 in validation and 0.94 in the test set, with ankle brachial index and lower limb discomfort among the informative features.(33) Specialized models address narrower clinical questions: a model for ulcer occurrence in patients with lower extremity arteriosclerotic occlusion reached an area under the curve of 0.96,(36)and an interpretable model predicted three-year ulcer recurrence with an area under the curve of 0.92 in 494 patients.(35)Healing phase classification from clinical and wound features has been proposed

to inform triage.(37) The convergence across these studies is that discrimination is high wherever the model is built; the divergence is in the predictors chosen, which differ from study to study, and in the near absence of external testing, which makes it unclear whether any single model transfers beyond its source hospital. The strongest counterexample in the axis is the differential diagnosis of diabetic foot infection from osteomyelitis, in which a LightGBM model using six routine blood biomarkers, age, glycated hemoglobin, creatinine, albumin, erythrocyte sedimentation rate, and sodium, was developed in 3,271 patients and validated externally in 341 patients from a second center, with an external area under the curve of 0.94 and a deployable web calculator.(34)This study demonstrates that external validation is feasible when investigators share data across centers, and it stands out precisely because the rest of the axis reports internal validation alone.

Beyond ulcer classification, models target the neuropathy and tissue stress that precede ulceration. Plantar pressure analysis with gradient boosting classified diabetic peripheral neuropathy with 100% accuracy in static assessment of 86 patients, with forefoot-to-hindfoot pressure ratio as a key feature.(38)In the same study, dynamic assessment reached 88% accuracy, a gap the authors attributed to the additional variability introduced by walking, and the static advantage held across the classifiers tested. A low-complexity model combined plantar pressure and temperature to distinguish polyneuropathy from healthy feet, using principal component analysis and maximum relevance minimum redundancy selection to keep computation light enough for ambulatory monitoring,(39)and thermal imaging with k-nearest neighbors has been applied to diabetic foot prediction.(40)A machine learning model developed on 1,544 patients and validated in an independent sample predicts diabetic peripheral neuropathy from clinical variables, which extends risk stratification to settings without specialized plantar pressure equipment.(41)A scoping review of artificial intelligence applied to foot thermography notes the fragmentation of algorithms and the focus on statistical performance rather than clinical implications.(10)A model combining corneal nerve imaging with clinical variables achieved an area under the curve of 0.94 for diabetic foot prediction with the addition of glycated hemoglobin alone, offering a screening route that does not depend on the foot itself.(32)Photographs from smartphones and tablets have likewise been combined with electronic health record attributes to predict ulcer healing in a podiatry wound clinic.(42)In that clinic, hand-crafted color and texture features outperformed both clinical attributes and deep features from a residual network, a reminder that simple engineered features remain competitive for wound photographs collected in routine care.

The axis also exposes a definitional divergence that affects comparability. The target outcome ranges from incident ulceration and ulcer recurrence to healing phase, infection, osteomyelitis, and major amputation, and each study selects its own definition and time window.(33-35,37)Reported performance is therefore not directly comparable across models, and the high areas under the curve should be read as upper bounds achieved within a single clinical setting. The practical consequence is that a podiatrist choosing a prediction tool today would find many internally validated candidates and almost no head-to-head evidence on which one transfers to their own population.

Diagnostic imaging and foot deformity classification

Radiographic measurement of foot deformities is repetitive and prone to interobserver variability, which makes it a natural target for automation. A deep learning solution automated weight-bearing foot measurements and was compared against manual reading by radiologists.(43)A heatmap-in-heatmap landmark model trained on 806 patients with more than 3,000 radiographs classified multiple foot deformities in a dual-center study.(44)A deep neural network automated the Hardy and Clapham classification of hallux sesamoid position on 1,554 radiographs and was validated on 113 consecutive patients.(45)Automated weight-bearing measurements with commercial artificial intelligence software have also been reported in skeletal radiology.(46)These studies converge on the conclusion that automated angle and landmark measurement approaches the reliability of expert manual reading, although none has yet linked automation to changes in surgical or conservative decisions. Interobserver variability in these manual measurements is the recurring justification for automation across the studies, and the dual-center and consecutive-patient designs used in several of them address the concern that high accuracy in one institution does not generalize.(44,45)

Portable measurement extends the same logic beyond the radiology workstation. A smartphone application measured the hallux valgus angle from radiographs displayed on a monitor, with three users of different training levels.(47)An artificial intelligence system diagnosed hallux valgus interphalangeus from anteroposterior radiographs through bone segmentation.(48)Classification of arch type, the most common pediatric concern, is addressed from several image sources:

deep learning distinguished pes planus from weight-bearing radiographs,(49)segmentation of weight-bearing lateral radiographs improved diagnosis of pes planus and pes cavus against observers,(50)equivariant networks classified foot arch type from plantar pressure images,(51) transformer encoders with Bayesian-optimized support vector machines classified flatfoot,(52)and vision transformers classified plantar footprints from RGB images.(53) Pediatric flatfoot detection with convolutional backbones was explicitly described as an under-researched area.(54)Statistical shape modeling of the subtalar joint from weightbearing computed tomography quantified the cavus-to-planus spectrum, which moves foot typing from qualitative judgment toward continuous morphology.(55)The axis is comparatively homogeneous in method, image-level classification with radiologic or observational ground truth, and comparatively weak in outcome evidence, since no study reported whether automated classification changed management. The measurement tasks in this axis are also the closest to regulatory clearance, because they reproduce an existing radiologic measurement rather than a new diagnostic claim, and several of the systems described here are commercial or near-commercial software evaluated against radiologists.(43,46) The remaining question is therefore less technical than clinical: whether automation reduces measurement time and interobserver disagreement in everyday podiatric clinics rather than in curated research sets.

Wearable sensing, smart dressings and remote monitoring

Continuous monitoring moves assessment out of the clinic, and the diabetic foot is the main target. A systematic review of smart wearable technology for diabetic foot prevention, assessment, and management identified sensing and smart miniaturized devices as an expanding field while noting the limited consolidated clinical evidence.(11)All-textile sensor arrays with bimodal pressure and humidity sensing have been proposed for early warning of ulcer formation,(56)and modular piezoelectric insoles support portable gait analysis and foot health monitoring.(57)

Sensor-enabled dressings close the loop between monitoring and treatment. An in vivo validated smart dressing embeds a pH-sensitive dye in a hydrogel sheet, so that the wound environment signals infection remotely, an approach motivated by the estimate that at least half of diabetic foot ulcers become infected.(3)The choice of pH rests on its status as a candidate marker of infection, which is otherwise invisible to a patient between clinic visits. A systematic review of digital health technologies for diabetic foot ulcers found promise for prevention, diagnosis, and management, while documenting access inequities in low- and middle-income settings.(12)

Fall risk assessment illustrates the breadth of wearable foot sensing beyond diabetes. Foot-mounted inertial waveforms from 146 older adults were clustered into four gait phenotypes with fall prevalence between 27% and 68%, supporting phenotype-specific prevention.(4)A wearable system discriminated a recessive weak foot gait pattern to refine individual fall risk estimates,(58) and plantar pressure sensors were evaluated for fall detection on sloped surfaces, alone and combined with inertial units.(59)These applications demonstrate feasibility, but their effect on falls or ulcer outcomes in routine podiatric practice has not been established. The axis is the least clinically mature of the five: hardware is abundant, while randomized or prospective evaluations of remote monitoring against usual care are essentially absent. The hardware layer has nonetheless matured, with self-powered triboelectric insoles, all-textile arrays, and pH-sensing dressings moving monitoring from laboratory prototypes toward wearable form factors that can be manufactured at low cost.(3,22,56)What the axis lacks is the clinical layer, prospective studies that compare continuous monitoring against periodic examination for ulcer prevention or fall reduction, and it is this layer, rather than any sensor shortcoming, that separates remote monitoring from routine care.

Validation, bias and clinical translation

Across the five axes, the recurring constraint is not algorithmic capacity but evidence of clinical validity. External validation remains the exception: only a minority of the foot models reviewed were tested outside their development center, and where they were, performance dropped, as in the amputation model that fell from an area under the curve of 0.93 internally to 0.83 externally.(30) This is consistent with the broader literature on artificial intelligence in medicine, which describes regulatory, interpretability, and interoperability barriers to adoption(60)and warns that biases can remain latent even in apparently fair models.(61)A fairness audit of convolutional networks for ulcer classification examined skin tone across three architectures and reported architecture-dependent accuracy, an audit of the kind that should become routine in this domain.(62)

Explainability is now reported as a routine companion to predictive accuracy. SHAP, LIME, and Grad-CAM feature in models for infection versus osteomyelitis,(34)amputation,(30)ulcer detection,(63)and ulcer identification.(26)These methods expose which inputs drive a prediction, but

none of the reviewed studies demonstrated that explanations change clinical decisions or outcomes. This is a specific instance of a wider gap, which reviews of artificial intelligence in diabetes summarize as a contrast between abundant technical demonstrations and scarce prospective, deployed systems.(8)The tension between predictive and explanatory modeling mirrors a broader debate in medicine, in which machine learning prioritizes accurate prediction while conventional statistics prioritize inference, and the two are not interchangeable.(6,64) Causal machine learning adds a related caution: a targeted maximum likelihood analysis of diabetic foot infection treatment found that observational data can simulate benefits from selection bias, which counsels against causal claims from prediction models alone.(65)The implication is not that prediction is useless, but that a model that predicts an outcome does not, by itself, justify a treatment decision, and the two purposes require different study designs.

Language models introduce a new channel through which patients and clinicians encounter podiatric information. ChatGPT-3.5 answered questions on diabetic foot ulcer care with high rated accuracy but omitted key details and presented some misinformation in one evaluation,(66) and a retrieval-augmented generative system was built to provide diabetes and foot care information at an eighth-grade literacy level with higher accuracy.(67) The contrast between the two is instructive: a general model answers from its training distribution, whereas a system anchored to retrieved medical knowledge reduces the risk of fabricated content, and the latter approach is the more defensible basis for patient education. Qualitative work with podiatrists indicates a clear preference for artificial intelligence in supportive roles over diagnostic roles, driven by concerns about trust and accountability.(68)

Reviews of the field converge on the same diagnosis. Systematic and narrative syntheses of artificial intelligence in chronic wounds,(13)in diabetic foot imaging,(69)and in diabetes care(8)all describe high internal accuracy with little prospective deployment, alongside data scarcity, inconsistent annotations, and bias. The convergence of independent reviews strengthens this conclusion rather than repeating it: the field has demonstrated what the algorithms can compute, and has not yet demonstrated what they change for patients. That conclusion applies with equal force to the diabetic foot, where the clinical stakes of acting on a wrong prediction are higher than in many other applications reviewed here.

DISCUSSION

The principal finding of this review is that artificial intelligence in podiatry has matured technically across the entire care continuum, from gait and plantar pressure analysis to diabetic foot risk prediction, while the evidence of clinical validity and prospective benefit has not kept pace. Across 65 synthesized studies, models report high internal discrimination, several with areas under the curve above 0.9, but external validation remains the exception and deployment studies are nearly absent. This pattern is the same one described in the wider medical literature, where machine learning outperforms conventional statistics in prediction tasks while wide clinical adoption lags.(6)The history of the field suggests that technical maturity precedes, and does not guarantee, clinical adoption.(5)

The findings align with and extend prior reviews. Syntheses of image-based diabetic foot diagnosis,(9)thermography,(10)and wearable diabetic foot technology(11)each reached a similar conclusion within their modality, and this review shows that the limitation is transversal rather than specific to any one technique. The observed attenuation from internal to external performance, exemplified by the amputation model that fell from 0.93 to 0.83,(30)matches the general problem of dataset shift described for artificial intelligence in medicine.(60)The review also confirms the call for fairness audits in wound imaging(62)and for causal rather than purely predictive inference in diabetic foot infection research.(65)In contrast to the dominant narrative that emphasizes accuracy, the qualitative evidence from podiatrists shows that trust, not discrimination, is the binding constraint on adoption.(68)

Several explanations account for the divergence between internal accuracy and clinical readiness. Most studies are retrospective and single-center, and their samples, ranging from 86 to 6,180 participants, are convenience samples drawn from one or a few hospitals.(33,38) Predictor sets differ across models, which complicates comparison and replication, and the outcome definitions for amputation and recurrence vary between studies.(28,35) Sensor-based systems introduce additional heterogeneity through hardware, sampling, and preprocessing choices.(11)These factors, rather than any single technical failure, explain why high reported performance has not translated into deployed tools. The exceptions, such as the two-center model differentiating infection from

osteomyelitis with external validation and a deployable calculator,(34)show what the next generation of studies must look like.

The mechanism behind external attenuation deserves emphasis, because it is not a defect of the algorithms but a property of the data. A model optimized on one hospital's case-mix learns that institution's prevalence, coding practices, and referral thresholds, and when these shift, the same coefficients no longer separate classes as cleanly. This is the dataset shift described for artificial intelligence in medicine at large,(60)and it is amplified in diabetic foot research by outcome heterogeneity, since major amputation, minor amputation, and recurrence are defined and counted differently across centers.(28,35) Calibration, the agreement between predicted risk and observed frequency, was reported in only a minority of the reviewed models, which compounds the problem, because a well-discriminating but miscalibrated model can misstate absolute risk and distort triage. The reviewed models that did report calibration, for example the amputation models that used Hosmer-Lemeshow statistics or Brier scores,(29,35) illustrate a practice that should become standard.

For podiatric practice the implications are specific. Automation of radiographic measurements and plantar pressure analysis is close to usable in the clinic, because these tasks replace repetitive measurement rather than clinical judgment, and the reliability evidence is consistent.(20,43) Risk prediction is less ready for autonomous use, and the preference of podiatrists for supportive roles is consistent with the appropriate deployment of these models as triage and documentation aids rather than decision makers.(68)Language models should be treated as patient-education adjuncts that require accuracy safeguards, given their variable performance on foot and ankle questions.(66,67) Any digital tool also needs to complement, rather than displace, the multidisciplinary care that diabetic foot and rehabilitation already require, which includes movement-based rehabilitation after ulcer healing.(70)In resource-limited settings, the priority is not the most accurate model but the most accessible one, since digital health technologies for the diabetic foot already show inequities in access.(12)

For the clinician, a practical reading of this literature is a three-part rule. Measurement automation, for angles and arch parameters, is reliable enough to adopt where validated software is available.(43)Prediction models can inform risk discussion but should not yet govern referrals or amputation decisions, given their external attenuation.(30)Language models and patient-facing tools require verification against sources, because their accuracy varies by question and by system.(66,67) This rule reflects the evidence as it stands and is reversible as prospective studies accumulate.

These tools also carry consequences for podiatric education and governance. The qualitative finding that podiatrists prefer supportive roles for artificial intelligence(68)implies that training should teach practitioners how to interpret model outputs, when to override them, and how to explain them to patients, rather than treating the model as an external authority. Governance follows the same logic: a tool that automates a radiologic measurement needs a different level of oversight than a tool that proposes a triage decision, and the two should not be regulated identically. The reviews that frame adoption in terms of regulatory, interpretability, and interoperability barriers(60)point toward a staged pathway, in which measurement automation is cleared first, decision support second, and autonomous diagnosis only after prospective evidence of safety.

These observations translate into concrete design standards. Future studies should report both discrimination and calibration, specify the outcome definition and its time window, and describe the population from which the sample was drawn well enough to judge transportability.(29,35) Models intended for screening should be tested prospectively against the clinical pathway they are meant to replace, and models intended for monitoring should be compared against periodic examination, not against no care at all. Benchmark datasets and shared evaluation protocols would let independent groups reproduce results, which the current single-center literature does not yet permit.(15,20) These standards cost less than the effort already invested in model development, and they are the shortest path from demonstration to deployment.

The review has limitations. First, the selection was narrative rather than systematic, so the study set reflects the documented searches and the thematic matrix rather than an exhaustive screen; the risk of missing relevant work is real, and the remedy is to repeat the search in living systematic reviews as the field grows.(14)A single author conducted the selection and synthesis, and although the decisions were recorded in the argument matrix, an independent second reader would reduce selection error. Second, searches were conducted with English terms in four databases, which may underrepresent non-English literature and regional journals. Third, performance figures were extracted from abstracts rather than full texts, so pooled comparisons across models were not performed and reporting could not be harmonized across studies. Fourth, publication

bias is plausible in this field, because negative or modest results are less likely to be published, which would inflate the impression of high accuracy. Each of these limitations carries a corresponding remedy: prospective registration and broader multilingual searches, full-text extraction with standardized reporting, and the publication of null results and benchmark datasets.

The research agenda that follows is concrete. External validation should become a condition for reporting foot and ankle models, and multicenter, prospective cohorts with harmonized outcome definitions should replace single-center retrospective designs.(30)Fairness should be reported across skin tone, sex, and age as a routine metric.(62) Implementation studies should measure whether these tools change triage, referral, ulcer healing, or amputation rates, rather than stopping at discrimination metrics.(13)Prospective registration of prediction models, together with the release of code and model weights, would allow independent verification of the reported discrimination. Finally, the deployment of wearable and remote monitoring systems requires evidence of usability and equity in low-resource settings(12)(Table 4).

Table 4. Limitations of the current evidence and corresponding recommendations.

Limitation	Recommendation
Single-center retrospective designs	Prospective multicenter cohorts with harmonized outcome definitions
Scarce external validation	Require external validation as a reporting condition
Bias in ulcer classification	Report fairness across skin tone, sex, and age
No evidence of clinical effect	Implementation studies measuring triage, healing, and amputation rates
Heterogeneous sensors and preprocessing	Standardized data and benchmark datasets
Access inequities in remote monitoring	Usability and equity studies in low-resource settings

Note: The recommendations are linked to each limitation as proposed in the discussion. Source: Own elaboration.

CONCLUSIONS

Automated gait analysis and biomechanical assessment can reconstruct plantar pressure and joint kinetics from wearable signals and can measure the foot arch with accuracy comparable to manual methods, although the evidence is mostly single-center proof of concept. Models for diabetic foot risk prediction and ulcer assessment report high internal discrimination, with areas under the curve between 0.89 and 0.97, and their performance attenuates on external validation, which currently limits clinical deployment. Diagnostic imaging and deformity classification, wearable sensing, and remote monitoring extend artificial intelligence across the podiatric care continuum but lack prospective evidence of benefit. The central barriers are scarce external validation, unresolved bias, and the absence of implementation studies, which define the agenda for the next stage of the field.

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