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REVIEW ARTICLE

Role of Artificial Intelligence in the Prevention and Management of Lifestyle-Related Disorders: Current Evidence and Future Perspectives

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Abstract

Background: Lifestyle-related non-communicable diseases cause most premature mortality worldwide, yet conventional preventive services remain poorly personalised, reactive and difficult to sustain. Artificial intelligence (AI) has been proposed as a remedy for each of these weaknesses. Objective: To critically evaluate published evidence on AI for risk prediction, lifestyle modification, monitoring and clinical management of lifestyle-related disorders, distinguishing established applications from preliminary, experimental and proposed ones. Methods: A structured, non-systematic search of PubMed/MEDLINE, Scopus, Web of Science, the Cochrane Library and IEEE Xplore was performed, prioritising randomised trials, systematic reviews, external validation and implementation studies published between 2018 and 2026 alongside earlier landmark trials and current reporting and ethics frameworks; clinical endpoints were weighted above technical performance. Findings: The strongest clinical evidence concerns algorithm-guided dietary strategies in dysglycaemia, where small randomised studies improved postprandial glucose and glycated haemoglobin. The weakest concerns obesity: a large randomised trial found that adding an activity monitor to a behavioural programme produced less weight loss than the programme alone. Prediction models for diabetes and cardiovascular risk are plentiful but seldom externally validated, calibrated or prospectively evaluated, and systematic appraisals judge most to be at high risk of bias. Conversational agents and consumer wearables promise engagement and monitoring, but measurement validity and outcome benefit remain unproven. Conclusion: AI has demonstrable technical capability and limited demonstrated clinical effectiveness in lifestyle medicine. Prediction is not prevention and accuracy is not benefit; progress now depends on prospective, pragmatic and equitable evaluation rather than further model development.

Keywords: Artificial Intelligence; Lifestyle-Related Disorders; Machine Learning; Preventive Healthcare; Personalized Medicine; Digital Health; Non-Communicable Diseases; Clinical Decision Support

Introduction

Non-communicable diseases caused an estimated 43 million deaths in 2021, roughly three-quarters of all non-pandemic-related mortality. Eighteen millions of these deaths occurred before age 70 years, and more than four-fifths of that premature mortality fell in low- and middle-income countries.[1] Raised blood pressure remains the largest metabolic contributor to attributable mortality, followed by hyperglycaemia and excess adiposity[1], and a pooled analysis of 3,663 population-representative studies documented rising obesity in most countries between 1990 and 2022.[2] Because the principal determinants are behavioural, the burden is in principle preventable.

That prevention works is not in doubt: intensive diet and activity counselling reduced incident type 2 diabetes by 58% in the Diabetes Prevention Program.[3] The difficulty is delivery. Structured programmes are labour-intensive, poorly scalable and lose adherence once supervision ends; risk is identified late, counselling is standardised rather than individualised, and the interval between visits is a blind spot in which behaviour and physiology change unobserved.

Artificial intelligence (AI) here denotes computational methods that infer patterns from data in order to classify, predict or generate outputs, not any particular product. Machine learning, deep learning, predictive analytics and language models differ in data requirements, interpretability and failure modes, and are not interchangeable. Four distinctions frame this review: a model that predicts disease does not thereby prevent it; discriminative accuracy does not establish benefit; digital health tools are not necessarily AI; and learned associations are not causal. WHO guidance on the ethics and governance of AI for health, most recently for large multi-modal models, situates such systems within health-system governance rather than outside it.[4]

This critical narrative review appraises what is established, preliminary or merely proposed across

obesity, type 2 diabetes, hypertension and cardiovascular risk, inactivity, diet and sleep. It is not a systematic review and makes no claim to exhaustive identification or quantitative synthesis.

Artificial Intelligence in Lifestyle Medicine: Concepts and Applications

Machine learning

Supervised learning maps predictors to a labelled outcome and underpins most risk models; unsupervised learning groups patients without a prespecified endpoint, for phenotyping. Whether these methods outperform regression is empirical: across 71 comparisons there was no evidence of superior discrimination for machine learning over logistic regression once analyses at low risk of bias were considered, and calibration was unaddressed in 79% of studies.[5]

Deep learning

Deep learning extracts hierarchical representations from images, waveforms and accelerometry, at the cost of opacity, sensitivity to distributional shift and heavy data requirements. Most reference standards in lifestyle medicine are surrogates, so a model may reconstruct a measurement accurately without improving any decision made from it.

Predictive analytics

Predictive analytics estimates individual risk to prioritise preventive effort. Discrimination summarises ranking, but calibration—agreement between predicted and observed risk—determines whether a probability can support a decision, and miscalibrated algorithms mislead precisely at intervention thresholds.[6]

Natural language processing and generative AI

Language models are used for patient education, coaching and documentation. In a cross-sectional study of 195 patient questions from a public forum, evaluators preferred chatbot responses to physician responses in 78.6% of assessments and rated them higher for quality and empathy.[7] This concerns plausibility and tone, not correctness in an individual case, and does not extend to diagnosis or prescribing; hallucination, inconsistent advice and inability to detect deterioration remain unresolved hazards.

Wearable technologies and digital health

Only part of the wearable analytic chain is genuinely AI: step counting and threshold-based sleep estimation are conventional signal processing, whereas learned models map raw waveforms to physiological states or adapt support to predicted behaviour. Among 3,077 adults, calibrated smartwatch models estimated blood pressure acceptably in younger, normotensive participants but deteriorated in older and hypertensive participants and without calibration.[8] Consumer sleep devices show high sensitivity for sleep, low-to-medium specificity for wake and inconsistent staging .[9] Dense measurement is not valid measurement.

Clinical Applications of AI in Lifestyle-Related Disorders

Obesity prevention and weight management

In 800 adults contributing 46,898 meals with continuous glucose monitoring, glycaemic responses to identical meals varied widely, and a model integrating clinical and microbiome features predicted personal responses better than meal composition alone.[10] This established a principle, not a treatment effect. In a crossover trial of 23 adults with newly diagnosed type 2 diabetes, an algorithm-derived postprandial-targeting diet lowered glucose-monitor-derived measures compared with a Mediterranean-style diet, and a six-month extension in 16 participants was associated with a 0.39% fall in glycated haemoglobin.[11] Small samples, short follow-up and surrogate endpoints limit inference, but this remains among the few randomised demonstrations that algorithm-guided dietary advice shifts a clinical intermediate outcome.

Against this stands the field's strongest negative trial. In IDEA, 471 adults with a body mass index of 25 to under 40 received a standard behavioural programme; from six months, one group also used a wearable with a web interface for self-monitoring. Over 24 months that group lost less weight (3.5 kg versus 5.9 kg; difference 2.4 kg).[12] The device was not AI-based, which is the point: feedback technology assumed to be beneficial was not. Whether adaptive, algorithm-driven support behaves differently is untested. PREDICT, characterising postprandial lipaemia and inflammation in over 1,000 adults, indicates that the rationale for personalisation extends beyond glucose.[13]

Type 2 diabetes prediction and management

A scoping review of machine-learning models for incident diabetes in primary care found that most

reported moderate-to-good discrimination, but external validation, calibration and prospective implementation were uncommon [14]—a structural problem, since models are typically developed and tested on one data source and reported without reference to the decision they inform. Management of established disease offers a better evidence profile because outcomes are measurable and data longitudinal.

Table 1. Artificial intelligence technologies and their potential applications in lifestyle medicine

AI technology	Healthcare application	Data requirements	Potential advantages	Limitations	Ref.
Supervised machine learning	Risk prediction; patient stratification	Structured clinical, laboratory and lifestyle variables with labelled outcomes	Handles many predictors and interactions; automates risk scoring	No consistent advantage over regression at low risk of bias; centres on discrimination rather than calibration	[5,6,17]
Unsupervised learning	Phenotyping; identification of high-risk subgroups	Multivariate patient data without outcome labels	Reveals structure not specified in advance; may replicate across datasets	Cluster validity uncertain; clinical meaning of clusters requires interpretation	[18]
Deep learning	Interpretation of images, waveforms and physiological signals	Large labelled datasets; raw signal or image input	Learns representations without manual feature engineering	Opaque; sensitive to distributional shift; reference standards are often surrogates	[8,9]
Predictive analytics / dynamic risk models	Incident disease and complication prediction; preventive targeting	Longitudinal electronic health record data	Uses routinely collected data; supports panel-level stratification	Rare external validation; model drift; decision impact rarely demonstrated	[14,15,16, 19,20]
Natural language processing and large language models	Patient education, conversational coaching, documentation	Text corpora; conversational data; clinical context	Scalable, acceptable to users, linguistically fluent	Hallucination; inconsistent advice; no reliable detection of clinical deterioration	[7,21,36]
Reinforcement learning and adaptive interventions	Just-in-time adaptive coaching for activity, diet and sleep	Dense behavioural time-series with proximal outcomes	Personalises timing and content of support	Largely at protocol and pilot stage; risk of optimising engagement rather than health	[22]

Dynamic models trained on electronic health records have predicted acute and chronic complications with external validation in a separate health system,[15] and a territory-wide model has identified older adults at high risk of severe hypoglycaemia.[16] Both target actionable events, yet neither has been shown prospectively to reduce them.

Hypertension and cardiovascular risk assessment

A systematic review applying a risk-of-bias tool judged all included machine-learning cardiovascular models to be at high risk of bias and assessed only a small minority as suitable for recommendation after validation screening.[17] Where rigorous validation exists, results are more encouraging: clustering of patients with heart failure across three record sources produced subtypes that replicated and carried prognostic and genetic signal.[18] A record-derived model has since been tested prospectively to guide atrial fibrillation screening,[19] though screening yield is not stroke reduction, and machine learning models have also been derived and compared for prediction of first emergency admission alongside conventional models using linked primary care data.[20]

Physical activity and behavioural modification

Activity monitoring is mature; adaptive coaching is not. Most commercial programmes deliver fixed goals and static feedback, and IDEA counsels against assuming that more feedback yields more activity.[12] Adaptive systems using reinforcement learning and language models remain at protocol stage: a randomised trial is testing an app-based assistant with device-measured activity as the primary outcome in 198 adults.[22] Engagement data indicate that patients accept AI-delivered coaching, with preferences varying between AI and human delivery;[21] acceptability is necessary but insufficient, and preference is not an outcome.

Sleep and stress-related health

The sleep literature usefully separates measurement from intervention. Consumer devices detect sleep acceptably and distinguish wake and stages poorly.[9] By contrast, fully automated digital cognitive behavioural therapy for insomnia has consistent randomised support: meta-analysis reports substantial reductions in insomnia severity,[23] multicentre trials replicate efficacy,[24] and app-delivered therapy has been evaluated for preventing major depressive disorder in young people,[25] with adherence modifying effects.[26] None of this shows that

the AI component contributes, since the active ingredient is structured cognitive behavioural therapy. Wearable-derived stress assessment remains the least validated.

Role of AI in Personalised Preventive Healthcare

Personalised prevention requires accurate individual risk estimation, identification of modifiable determinants, and an intervention the person will sustain. AI can contribute to each with differing support. Population-level stratification integrating records, laboratory and patient-generated data is feasible and is where health-system interest lies; adaptive recommendation conditioned on observed behaviour is plausible and partly supported;[10,11] continuous monitoring closes the loop between visits, within the limits of measurement validity.[8,9]

Reliability depends on representative development data, calibration with periodic updating, external validation in the intended deployment population, and prospective evidence that acting on the recommendation changes an outcome. Tailored advice is not, by virtue of being tailored, validated precision medicine, and it cannot substitute for clinical judgement: risk interacts with comorbidity, preference, cost and social circumstance in ways no model encodes. AI-supported recommendations should inform a clinical conversation, not replace it.

Potential Mechanisms Through Which AI May Improve Lifestyle Management

AI is not a biological treatment: it exerts no direct physiological effect and cannot itself reduce adiposity or blood pressure, so benefit must be mediated through decisions and behaviour. Five pathways are proposed, each separately testable. Improved risk identification allows earlier, better-targeted prevention and more efficient use of scarce capacity. Personalised feedback conditioned on monitored activity and physiology may be more actionable than generic advice. Continuous monitoring may detect trends between visits, if measurements are valid. Engagement through reminders, goals and coaching may reduce attrition, although technology can also displace effective components.[12] Clinical decision support shifts the mechanism from patient behaviour to prescriber behaviour. These pathways are proposed, not demonstrated, and their failure modes differ: an intervention that fails to engage and a model that is miscalibrated both fail, for unrelated reasons.

Clinical Evidence, Model Performance, and Real-World Effectiveness

Discrimination summarises ranking; calibration summarises the accuracy of the probability, and threshold-based decisions depend on the latter.[6] Internal validation estimates performance within the development distribution, only external validation tests transportability, and only prospective evaluation tests whether decisions change. That sequence is frequently truncated, as reviews of diabetes and cardiovascular models show.[14,17] Reporting frameworks now make the distinctions explicit: TRIPOD+AI for prediction model studies[31], PROBAST+AI for risk of bias[32], CONSORT-AI and SPIRIT-AI for trials and protocols [28,29], and DECIDE-AI for early clinical evaluation.[27] Adherence remains partial; published randomised trials of AI interventions showed median concordance of 90% with CONSORT-AI items, leaving a material proportion unreported.[30] PRISMA 2020 and SANRA informed the reporting and quality criteria consulted here without being applied as formal instruments to this narrative review.[33,34]

Outcome evidence is what the literature lacks. Few studies report whether AI-supported interventions improve adherence beyond the short term, produce meaningful risk-factor change, reduce incident disease or lower costs. Where benefit has been shown, the comparator was another active intervention or a waiting list, follow-up spanned weeks to months, and the algorithm's specific contribution was not isolated.[11,23]

Ethical, Regulatory, and Implementation Challenges

Lifestyle data are intimate, continuous and often generated outside clinical settings by commercial platforms whose terms differ from those of health systems; consent at device setup rarely anticipates secondary use for model training. India's Digital Personal Data Protection Act, 2023 imposes consent- and purpose-based obligations on such processing, and software making diagnostic or treatment claims falls under medical device regulation, but no application discussed here should be assumed to hold regulatory approval in any jurisdiction.

Bias is not hypothetical. A commercial risk-stratification algorithm affecting millions underestimated illness in Black patients because it predicted costs rather than need; correcting the target variable would have raised the proportion identified for additional support from 17.7% to 46.5%.[35] The mechanism—a convenient proxy substituted for the construct of interest—recurs wherever lifestyle data are used, since access to trackers, facilities and healthy food is itself socially patterned. Further challenges include transparency where decisions affect individuals, accountability for harm, cybersecurity, interoperability between consumer platforms and records, digital literacy and cost. Generative systems add a distinct hazard: plausible but incorrect dietary or exercise advice delivered at scale to patients with renal, cardiac or eating disorders, with documented variability in the appropriateness of language-model nutritional advice.[3] WHO guidance on large multi-modal models sets expectations for oversight and transparency rather than certification.[4]

Future Perspectives and Emerging Research Directions

Several developments are plausible within the coming decade. Multimodal models combining activity, sleep, glycaemic and record data could improve discrimination over single-source models if incremental value is demonstrated rather than assumed. Explainability may support trust and error detection, though post-hoc explanation is no guarantee of validity. Federated learning would allow training across institutions without pooling identifiable data, which matters where sharing is legally constrained. Digital biomarkers may mature into monitoring tools if validated against clinical reference standards, and adaptive interventions formalised as sequential decision problems offer a principled framework for deciding when to intervene. Integration into electronic health records, and community deployment through primary care and community health workers, are the routes by which any of this reaches populations rather than research participants. What is required is a different evidentiary standard—multicentre validation, pragmatic trials with patient-centred endpoints, cost-effectiveness analysis and deliberate evaluation in the most affected populations—rather than more model development.

Research Gaps and Methodological Limitations

The literature is dominated by retrospective development on convenience samples, often single-centre and small. External validation is uncommon and frequently uses a random split of the same dataset, which does not test transportability. Outcome definitions vary, comparators are weak or absent, and follow-up is short. Reporting of predictor handling, missing data and model selection is often incomplete, and data leakage and overfitting are inconsistently addressed. Implementation research—workflow fit, alert burden, equity of uptake, safety incidents—is scarce. Improvement requires prospective registration, adherence to TRIPOD+AI and PROBAST+AI, calibrated reporting with decision-curve analysis, and trials designed around outcomes that matter to patients.

Discussion

A coherent pattern emerges. The applications with the most convincing clinical evidence are those in which the algorithm personalises an intervention of established efficacy and the outcome is a proximate physiological measure. Algorithm-guided dietary strategies in dysglycaemia fit this description: dietary change is known to work, the algorithm selects among effective options, and the endpoint is measurable within weeks.[10,11] Automated digital cognitive behavioural therapy fits it too, though there the benefit derives from the therapy rather than from adaptivity.[23,24] Applications that remain primarily predictive—diabetes risk scores, cardiovascular models, complication and hypoglycaemia prediction—have plausible value but little outcome evidence and uneven methodological quality.[14,15,16,17] Adaptive activity coaching and wearable stress assessment remain experimental.[22] The obesity field is instructive because it contains a well-powered negative trial of technological augmentation, which should temper the assumption that more data and more feedback improve behaviour.[12]

Three implications follow. Technological innovation is not clinical improvement: the binding constraints are adherence, social context and service capacity, and an algorithm addressing none of them is unlikely to change outcomes. Clinician oversight and patient engagement are the mechanism through which benefit is realised, which places workflow integration and acceptability at

the centre of evaluation rather than at its end. Finally, the equity argument cuts both ways: where rationing of preventive capacity is the binding problem, stratification supported by simple, well-calibrated models may yield population benefit, yet the infrastructure, connectivity, language coverage and local validation required for elaborate systems are precisely what such settings lack. AI is more likely to incrementally improve targeting and personalisation where systems can absorb it than to substitute for the behavioural and structural determinants of lifestyle-related disease.

Conclusion

Artificial intelligence offers credible technical capability in lifestyle medicine: risk estimation, personalised dietary prediction, signal interpretation and conversational support are all demonstrable. Demonstrated clinical effectiveness is far narrower, largely confined to small randomised studies of algorithm-guided dietary advice in dysglycaemia and to digitally delivered behavioural therapies whose active ingredient is not the algorithm. Prediction models are abundant but rarely externally validated, calibrated or prospectively evaluated, and appraisals continue to find high risk of bias; fairness, privacy, safety and equitable access remain unresolved. AI cannot independently prevent or cure lifestyle-related disorders. Its realistic contribution is to make existing preventive and therapeutic effort better targeted, more individualised and more continuously supported—a claim that must be tested in prospective trials with patient-relevant endpoints rather than asserted from model performance.

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