

Review

AI for Primary Prevention and Longevity: From Reactive to Proactive Healthcare Model

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Abstract

Primary prevention is essential to reduce disease burden before clinical onset, yet it remains less systematically integrated into care than diagnosis and treatment. Although artificial intelligence (AI) is increasingly used in medicine, most applications have focused on secondary and tertiary prevention, including diagnosis, prognostic stratification, and disease management, while its role in primary prevention remains less defined. This narrative review examines current AI applications across four modifiable lifestyle domains relevant to prevention and healthspan promotion: nutrition, physical activity, sleep, and mental health. We synthesize evidence on machine-learning models, wearable-derived algorithms, computer-vision tools, just-in-time adaptive interventions, and conversational agents used in consumer, community, and hybrid clinical-digital settings. AI applications support postprandial glycemic prediction, automated dietary assessment, meal-planning adherence, sedentary-pattern detection, personalized exercise recommendations, adaptive behavioral nudges, sleep monitoring, circadian-aware recommendations, psychoeducation, stress-management support, and early identification of psychological vulnerability. Collectively, these tools may extend prevention beyond episodic clinical encounters toward continuous, personalized, and context-aware support. However, evidence remains limited by short follow-up, reliance on surrogate or engagement outcomes, digitally literate populations, and insufficient validation in real-world preventive-care pathways. AI is therefore a promising enabling technology for proactive, healthspan-oriented medicine, provided future studies demonstrate long-term effectiveness, equity, safety, and responsible implementation.

Keywords: primary prevention; longevity; artificial intelligence; preventive medicine; digital health; personalized medicine



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1. Introduction

Preventive medicine is a cornerstone of public health, aiming to reduce disease burden and improve population well-being by intervening before, during, or after the clinical manifestation of disease. It is traditionally stratified into three levels. Primary prevention seeks to avert the onset of disease by reducing exposure to risk factors and strengthening individual resilience in otherwise healthy populations; examples include vaccination campaigns, nutritional education, and the promotion of physical activity. Secondary prevention focuses on early detection and prompt management of incipient disease, with mammographic screening, hypertension monitoring, or lipid assessment as classical cases. Tertiary

prevention, by contrast, is directed toward established disease, aiming to mitigate complications and improve quality of life, as exemplified by cardiac rehabilitation post-myocardial infarction, physiotherapy after cerebrovascular events, or strict glycemic control in diabetes to prevent micro- and macrovascular damage [1]. Among these levels, primary prevention is the most upstream and potentially transformative, because it targets disease risk before pathology becomes clinically evident.

In recent years, AI has been increasingly applied in preventive medicine. However, most current applications remain concentrated in secondary and tertiary prevention, especially within hospital settings where structured datasets facilitate model training and validation. Examples include AI-assisted screening for diabetic retinopathy or malnutrition in secondary prevention [2,3], and AI-supported cardiac rehabilitation after myocardial infarction in tertiary prevention [4]. AI has also demonstrated utility in diagnostic imaging [5,6], prognostic stratification, and complication management [7].

These contributions are clinically relevant, but they largely operate within a disease-centered and reactive paradigm, in which AI supports detection, classification, or management after damage or clinical disease has already emerged. Conversely, the domain of primary prevention, although comparatively underexplored, offers a unique opportunity for AI to reshape healthcare by acting upstream of disease onset. By integrating continuous physiological monitoring, behavioral tracking, and multimodal data analysis, AI systems can identify subclinical risk markers and deliver personalized, context-aware interventions [8]. Recent evidence indicates that AI-based tools can enhance health promotion strategies targeting nutrition, physical activity, and behavioral change, thereby supporting the prevention of noncommunicable diseases (NCDs) [9–12].

Among modifiable determinants of health, four interrelated domains emerge as pivotal for primary prevention: nutrition, physical activity, sleep, and mental health. These domains are not isolated behavioral targets but biologically interconnected drivers of cardiometabolic, neurocognitive, and psychological resilience across the life course. In the field of nutrition, AI has enabled precision nutrition approaches through the integration of multi-omics data, computational models of nutrient–gene interactions, and digital platforms for dietary adherence. Examples include ML models capable of predicting post-prandial glycemic responses and computer vision systems for automated food recognition and portion estimation [13,14]. In physical activity, wearable-assisted monitoring combined with adaptive algorithms allows detection of sedentary patterns and the delivery of personalized feedback [15–17]. Just-in-Time Adaptive Interventions (JITIs) exemplifies how context-aware nudges can promote sustainable increases in daily activity levels [18,19]. Regarding sleep, AI-enhanced digital biometrics from wearables and smartphone-based sensors can accurately perform sleep staging, detect disorders such as obstructive sleep apnea, and identify circadian rhythm disruptions associated with cardiometabolic and neurocognitive risk [20–23]. Finally, in the domain of mental health, conversational agents and AI-driven mobile applications have been developed to provide stress management support, cognitive behavioral strategies, and resilience training [24,25]. Recent trials have shown modest reductions in distress and improvements in well-being, although effects remain heterogeneous and appear strongly dependent on intervention design, user engagement, and clinical context [26,27].

This narrative review aims to critically evaluate the role of AI in advancing primary prevention across the four domains of nutrition, physical activity, sleep, and mental health. Rather than focusing on AI as a tool for diagnosis or disease management, this review examines how AI may support earlier risk identification, personalized behavioral guidance, and continuous health promotion before disease onset. By synthesizing current evidence, identifying methodological limitations, and outlining future research directions, the re-

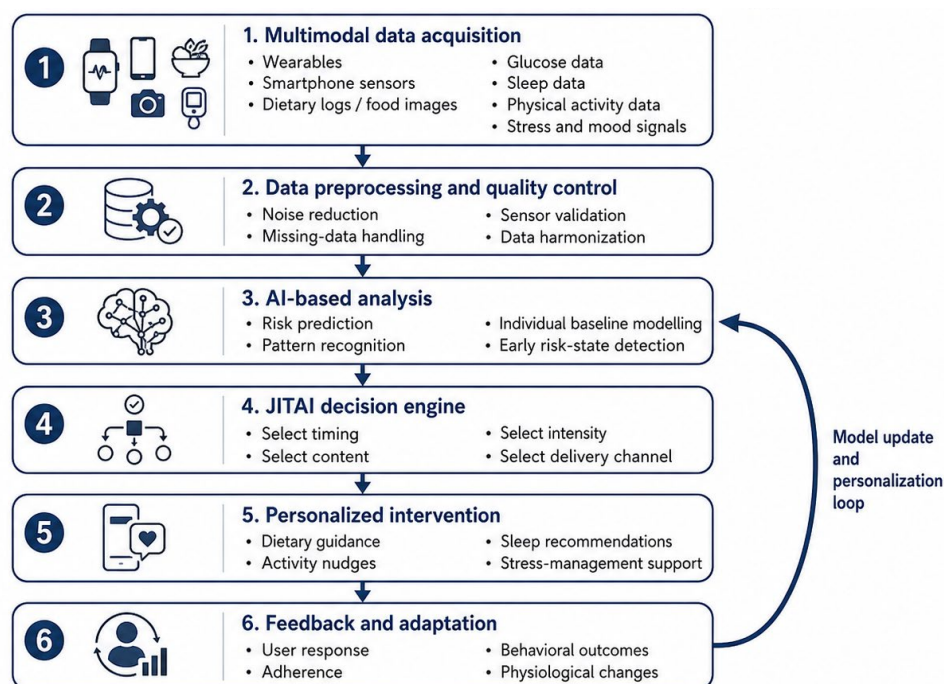
view situates AI within the broader framework of longevity and health span promotion and explores its potential to facilitate the transition from reactive healthcare to proactive, prevention-centered medicine.

2. AI in Preventive Medicine: From Reactive to Proactive Models

Historically, the application of AI in medicine has been largely concentrated in diagnostic and prognostic domains, corresponding to the secondary and tertiary levels of prevention. Early developments in AI focused on medical imaging, pattern recognition, and clinical decision support systems designed to detect disease, classify pathological findings, or estimate prognosis once a clinical condition was already suspected or established. ML and deep learning (DL) algorithms have achieved remarkable accuracy in radiology [28,29], pathology, and cardiology—detecting malignancies on imaging scans [30,31], classifying arrhythmias from electrocardiograms [32], and forecasting clinical deterioration in hospitalized patients [33]. These advancements have enhanced diagnostic precision, risk stratification, and treatment optimization. However, despite their sophistication, such applications remain embedded in reactive models of care, intervening after disease onset rather than preventing it. In this sense, much of current medical AI has improved the speed and accuracy of disease management but has not yet fully transformed the timing of intervention.

In contrast, the emerging frontier of AI-driven primary prevention emphasizes early detection of risk states and continuous promotion of health through proactive, individualized strategies. By integrating digital biometrics, behavioral tracking, and multimodal data streams from wearables, mobile sensors, and digital health platforms, AI can identify subtle deviations from healthy baselines before clinical disease manifests. Rather than relying only on fixed population thresholds, these systems can learn about an individual's longitudinal profile and detect changes that may be clinically meaningful for that specific person. Predictive models can forecast long-term risk trajectories, while adaptive algorithms deliver personalized feedback that supports behavior modification in real time. This shift is central to proactive medicine: prevention becomes less dependent on episodic clinical encounters and more embedded in everyday life, where risk accumulates and behavior actually occurs.

A key conceptual innovation supporting this transition is the emergence of JITAI, AI-driven systems that provide context-aware, moment-specific guidance based on an individual's current physiological state, behavior, and environment. Unlike conventional digital health tools, which often deliver generic reminders or static recommendations, JITAI is designed to adapt the timing, content, and intensity of the intervention to the user's real-time context. JITAI frameworks enable dynamic, responsive health promotion by delivering the right intervention at the right time, such as promoting physical activity after a period of inactivity [34], encouraging healthier food choices before meals [35], or prompting relaxation techniques during stress episodes [36]. Through continuous learning and personalization, AI thus shifts preventive medicine from episodic, population-based approaches toward a dynamic, data-informed model of proactive health management, where prevention becomes an ongoing, adaptive process integrated into everyday life. This adaptive logic is particularly relevant for primary prevention, where the clinical objective is not only to identify risk but also to influence repeated daily behaviors before risk consolidates into disease. This closed-loop logic of multimodal data acquisition, AI-based risk modelling, JITAI decision-making, personalized intervention, and feedback-based adaptation is summarized in Figure 1.



Multimodal data are processed through quality-control steps, analyzed by AI models, translated into context-aware JITAI decisions, and used to deliver personalized preventive interventions. User responses and physiological or behavioral changes are continuously fed back into the system to refine future recommendations.

Figure 1. Conceptual closed-loop framework for AI-supported primary prevention.

3. AI for Primary Prevention in Key Lifestyle Domains

3.1. Nutrition

AI is expanding the capacity to develop, deliver, and continuously refine personalized dietary recommendations. By integrating genomics, metabolomics, behavioral science, and digital health data, AI enables precision nutrition that accounts for individual variability in metabolism, lifestyle, and preferences [37,38]. This approach is a meaningful departure from population-level guidelines, which remain essential for public health but cannot capture interindividual differences in metabolic response and dietary adherence [39,40]. Table 1 provides a visual summary of the AI approaches applied to nutrition discussed below, comparing data inputs, prevention-related benefits, limitations, and performance variability in real-world settings.

Table 1. Comparative summary of AI technologies for nutrition-focused primary prevention.

AI Method/Technology	Preventive Use and Performance Variability	Main Advantages	Main Limitations/Risks
Multi-omics precision nutrition models (ML/DL)	Estimate individualized metabolic responses using microbiome, genomics, metabolomics, CGM and dietary records. Performance depends on cohort diversity, data quality and external validation.	Highly personalized; integrates heterogeneous biological data; may identify early dysmetabolic patterns before overt cardiometabolic disease.	Costly and data-intensive; limited standardization across omics pipelines; privacy and reproducibility concerns.

Table 1. Cont.

AI Method/Technology	Preventive Use and Performance Variability	Main Advantages	Main Limitations/Risks
Predictive risk models and interpretable ML (e.g., XGBoost with SHAP)	Predict obesity, diabetes or cardiovascular-risk profiles using health-examination, biochemical and lifestyle variables. Performance varies by feature availability, calibration and validation design.	Identifies modifiable predictors and supports individualized preventive recommendations; SHAP improves transparency for clinicians and users.	Risk of overfitting or population-specific bias; clinically meaningful thresholds and prospective testing are still needed.
Reinforcement-learning and recommender systems for meal planning	Adapt meal plans using recipes, nutritional targets, user preferences and feedback. Performance depends on engagement, reward definition and database quality.	Optimizes recommendations for adherence and feasibility, not only nutritional adequacy; supports iterative personalization.	Often evaluated in simulations or retrospective datasets; reward functions may oversimplify long-term health outcomes.
Computer vision for image-based dietary monitoring	Recognize foods and estimate portions from photographs or depth cues. Performance varies by food type, culture, image quality and database coverage.	Reduces the burden of self-reporting and enables granular monitoring of dietary intake in daily life.	Less accurate for mixed dishes, poor images and culturally specific foods; portion estimation remains challenging.
Conversational AI and JITAI nutrition support	Deliver education, goal setting and moment-specific nudges through chatbots, app logs and contextual triggers. Performance varies with engagement, timing and personalization.	Provides continuous behavioral support and may address health-literacy barriers between clinical encounters.	Evidence is usually short-term; risk of generic or unsafe advice without qualified oversight and escalation pathways.

3.1.1. AI-Driven Precision Nutrition: From Microbiome to Metabolomics

ML models can integrate and interpret complex multi-omics datasets to generate individualized, real-time dietary recommendations [41–43]. Liu Y-Y (2025) demonstrated how deep learning architectures (e.g., ODE, mNODE, McMLP, and METRIC) enable prediction of microbial composition and metabolic profiles, correction of errors in nutritional data, and estimation of individual metabolic responses to specific foods [44]. Because gut microbiome composition varies substantially across individuals, such models allow dietary guidance to be grounded in a person’s unique biological profile rather than population averages. Computational nutrigenomics further refines this approach by exploring gene–nutrient interactions [45,46], while metabolomic profiling and continuous glucose monitoring allow real-time analysis of postprandial glycemic responses [47,48]. ML models processing these continuous data streams can accurately predict glycemic excursions, identify foods that minimize glucose variability, and recommend individualized dietary adjustments [49–51]—capabilities particularly relevant to primary prevention, where early dysmetabolic patterns represent actionable targets before overt cardiometabolic disease develops.

3.1.2. Predictive Models and Adaptive AI for Personalized Dietary Planning

AI can identify individuals at elevated risk for obesity, type 2 diabetes, and cardiovascular disease based on dietary and metabolic patterns. Du et al. (2024) developed an ML-based obesity risk prediction system using health-examination data encompass-

ing lifestyle factors, body composition, and biochemical markers [52]. Among ten tested models, XGBoost achieved the best predictive performance; SHAP analysis identified hip circumference, fat mass, dietary habits, and triglycerides as the strongest predictors, translating heterogeneous data into interpretable, individualized risk profiles. Deployed as an online platform, the system allows users and clinicians to input personal data and receive targeted intervention suggestions before obesity-related complications emerge.

Adherence prediction adds a further layer of clinical utility: algorithms can assess which meal plans an individual is most likely to sustain long-term, enabling recommendations that are not only nutritionally optimal but also behaviorally realistic. Amiri et al. (2024) introduced CFRL (Collaborative Filtering Reinforcement Learning), which combines reinforcement learning and collaborative filtering within a Markov decision process framework to generate adaptive, user-accepted meal plans [53].

A human-in-the-loop mechanism allows real-time refinement based on user feedback, acknowledging that dietary personalization is as much a behavioural challenge as a biological one. Tested on a large dataset of recipes and user interactions, CFRL outperformed traditional methods in user satisfaction, nutritional adequacy, and adherence.

Generative AI extends these principles to consumer-facing tools: Microsoft Copilot uses optimization algorithms to automatically generate weekly menus aligned with nutritional goals, preferences, and budget constraints [54]. However, such tools should currently be regarded as supportive planning aids rather than clinically validated interventions, pending rigorous evaluation of their long-term impact on health outcomes.

3.1.3. Computer Vision for Image-Based Dietary Monitoring

Deep learning models, principally CNNs, can recognize foods from images, estimate portion size and volume, and link identified items to nutritional databases to calculate macro- and micronutrient intake. Compared with traditional self-reported food diaries, this approach reduces user burden and improves monitoring granularity, although accuracy depends on image quality, food complexity, and database completeness. Chotwanvirat et al. (2024) reviewed recent advances in this field, documenting how CNNs have improved food recognition and portion estimation through pixel density analysis, geometric modeling, 3D reconstruction, and depth cameras [55]. LogMeal (AIGecko Technologies S.L., Barcelona, Spain) applies CNN-based models to identify thousands of food items from images, estimate portion sizes, and calculate nutritional composition in real time [56].

3.1.4. Conversational AI and Behavioral Nutrition Support

Natural Language Process (NLP)-based chatbots and virtual assistants can deliver personalized dietary education, interpret nutrition labels, address health literacy barriers, and support behavior change by helping users identify obstacles to healthy eating and set realistic goals. SlimMe, a weight-management chatbot integrating NLP and affective computing, estimates daily caloric needs, tracks food and exercise, and delivers motivational support through adaptive language and visual cues via the LINE messaging platform [57]. While evaluated only in a preliminary simulation with a limited sample, it illustrates how emotional responsiveness may improve engagement and adherence within broader nutrition-support programs.

AI systems can further support primary prevention through JITAIs, delivering context-sensitive nudges at behaviorally relevant moments—for example, before grocery shopping or during recognized risk behaviors such as late-night snacking or stress-related eating [58]. Together, conversational AI and JITAI approaches transform dietary support from episodic advice into continuous, individualized behavioral guidance. Their preventive value, how-

ever, will require validation through longitudinal studies and appropriate integration with qualified dietary care.

3.2. Sleep

Sleep medicine is increasingly adopting AI-driven technologies that extend assessment beyond laboratory diagnostics and support a shift from reactive treatment toward primary prevention. By integrating multimodal data from wearable sensors, digital phenotyping, and longitudinal behavioral monitoring, AI systems can identify individuals at risk of poor sleep, support personalized interventions, and promote healthy sleep behaviors before chronic disorders develop. Table 2 summarizes the principal AI technologies used in preventive sleep medicine, contrasting their strengths, limitations and sources of performance variability.

Table 2. Comparative summary of AI technologies for preventive sleep-health applications.

AI Method/Technology	Preventive Use and Performance Variability	Main Advantages	Main Limitations/Risks
Conversational sleep coaching and digital CBT-1	Use sleep diaries, self-reports and app interactions to deliver sleep hygiene and CBT-1 components. Outcomes vary with engagement, baseline severity and follow-up duration.	Scalable behavioral support; may help modify maladaptive sleep habits before chronic insomnia develops.	Often relies on self-reported outcomes; adherence may decline; not a substitute for clinical assessment in severe cases.
Predictive ML for sleep-disorder risk assessment	Estimate risk using lifestyle, stress, depression, diet, sedentary behavior and demographics. Performance varies across algorithms, feature sets and populations.	Identifies modifiable risk factors and translates them into early preventive recommendations.	Population-specific training data may limit generalizability; external validation and calibration are often limited.
Wearable AI for sleep staging and recovery monitoring	Analyze accelerometry, PPG, HRV, temperature and oximetry to estimate sleep architecture or recovery. Accuracy varies by device, sensor placement, sleep stage and reference standard.	Enables passive, longitudinal monitoring outside sleep laboratories; useful for trend detection and preventive surveillance.	Less definitive than polysomnography; vulnerable to sensor noise, device heterogeneity and missing data.
Circadian and chronobiological analytics	Infer rhythm regularity and possible circadian misalignment from sleep timing, activity, temperature and contextual data. Applicability depends on continuous sampling and interpretable feedback.	Extends prevention beyond sleep duration toward rhythm alignment, relevant to cardiometabolic and cognitive risk.	Circadian state is difficult to infer from consumer sensors alone; environmental confounding may be substantial.
JITAI for sleep behavior change	Deliver timely nudges based on bedtime routines, contextual triggers and real-time behavioral patterns. Effectiveness varies with trigger accuracy, prompt timing and retention.	Intervenes close to the behavioral moment and adapts recommendations to daily routines.	Risk of notification fatigue; optimal timing, frequency and intervention dose remain uncertain.

3.2.1. AI-Based Conversational Sleep Coaching and Digital CBT-I

AI-powered conversational agents using NLP are increasingly employed to deliver personalized sleep coaching through digital sleep diaries and daily interactions. Reported

engagement rates reach 86%, with over 90% of users describing improved sleep quality and high satisfaction [59]. Although these outcomes mainly reflect self-reported measures, they demonstrate the feasibility and acceptability of AI-supported behavioral interventions.

Most platforms incorporate Cognitive Behavioral Therapy for Insomnia (CBT-I) principles [60,61], including stimulus control, sleep hygiene education, relaxation techniques, and cognitive restructuring. Sleepio (Big Health Inc., San Francisco, CA, USA) [62] exemplifies this approach by combining automated CBT-I modules with sleep tracking, relaxation exercises, personalized feedback, and adaptive recommendations. As CBT-I remains the first-line treatment for insomnia, digital delivery represents one of the most mature applications of AI-assisted behavioral sleep medicine.

From a primary prevention perspective, these systems may help users recognize and modify maladaptive sleep habits before transient disturbances progress to chronic insomnia or contribute to cardiometabolic and psychological disease.

3.2.2. AI-Driven Predictive Modeling for Sleep Disorder Risk Assessment

Machine learning models can integrate behavioral, lifestyle, and psychological variables to identify individuals at increased risk of sleep disorders before clinical symptoms emerge. Zhang et al. (2024) developed an AI platform using data from 2243 university students and compared six algorithms, including Extreme Gradient Boosting Machines (eXGBM), decision trees, KNN, random forests, neural networks, and support vector machines [63]. eXGBM achieved the best performance, with stress, depression severity, vegetable intake, age, and sedentary behavior identified as the strongest predictors through SHAP analysis.

Beyond predictive accuracy, the platform translated these factors into individualized risk scores and personalized recommendations targeting stress management, diet, and sleep hygiene. Such approaches illustrate how AI can support preventive sleep medicine by identifying modifiable risk factors and enabling early behavioral intervention.

3.2.3. Wearables, Circadian Monitoring, and Chronobiological Optimization

AI-enhanced wearable devices enable continuous monitoring of sleep patterns outside specialized sleep laboratories, providing longitudinal data that may support preventive sleep-health surveillance. The ŌURA Ring (Ōura Health Ltd., Oulu, Finland) [64] integrates accelerometry, photoplethysmography-derived heart rate and heart rate variability, and temperature sensing to estimate sleep architecture and physiological recovery.

Validation against polysomnography by de Zambotti et al. (2019) demonstrated good agreement for total sleep time and sleep efficiency, supporting its use for longitudinal monitoring rather than definitive diagnosis [65]. Continuous assessment of sleep timing and recovery may facilitate early identification of suboptimal sleep patterns and circadian disruption in everyday settings.

This capability is particularly relevant because chronobiological evidence indicates that circadian alignment, in addition to sleep duration, is essential for metabolic and cognitive health. Misalignment between internal biological rhythms and environmental cues impairs glucose regulation and increases cardiometabolic risk [66,67]. Consequently, AI-enabled wearables may contribute to primary prevention by detecting behavioral and circadian alterations before clinically significant sleep disorders develop.

3.3. Physical Activity

Regular physical activity is a cornerstone of primary prevention, reducing the risk of cardiovascular disease, type 2 diabetes, obesity, several cancers, and mental disorders [68]. Despite strong evidence supporting its health benefits, physical inactivity remains highly prevalent worldwide [69]. AI is increasingly being applied to address barriers to exercise

participation by delivering personalized, adaptive, and scalable interventions that integrate physiological, behavioral, and contextual information. Rather than providing generic recommendations, these technologies aim to optimize exercise prescription, monitor recovery, and support long-term adherence to healthy movement behaviors. Table 3 provides a structured comparison of the main AI approaches used for physical-activity promotion, exercise personalization and recovery monitoring.

Table 3. Comparative summary of AI technologies for physical-activity promotion and exercise personalization.

AI Method/Technology	Preventive Use and Performance Variability	Main Advantages	Main Limitations/Risks
ML-based personalized exercise prescription	Tailor training using age, baseline fitness, goals, preferences and health status. Performance varies with input completeness, baseline risk and adherence.	Moves beyond generic guidelines by adapting exercise to individual capacity and goals.	Clinical endpoints are often under-evaluated; safety constraints are needed for high-risk users.
Reinforcement learning for adaptive training progression	Adjust intensity, frequency and progression using performance, fatigue, recovery status, HRV and feedback. Effectiveness depends on reliable feedback and reward design.	Supports dynamic load management and may reduce both inactivity and overtraining.	Reward functions may not capture long-term health outcomes; requires frequent and high-quality data.
Pose-estimation and augmented-reality movement feedback	Assess posture, range of motion and execution from camera or depth-sensor data. Accuracy varies by exercise, viewpoint, lighting and user characteristics.	Provides immediate technical feedback during unsupervised exercise and may improve confidence and safety.	Privacy concerns; performance can be affected by camera setup, clothing and body type; injury-prevention evidence remains limited.
Wearable-derived digital biomarkers for activity and recovery	Use HR, HRV, accelerometry, sleep quality, soreness and performance trends to estimate intensity, adaptation and recovery. Performance varies by device, activity type and personalization.	Enables passive monitoring of movement and physiological adaptation; supports individualized recovery recommendations.	Sensor noise, device heterogeneity and missing data may bias recommendations.
Conversational AI, gamification and adaptive nudges	Use activity logs, sedentary-pattern detection, dialogue and behavioral preferences to support motivation. Effects vary with baseline motivation, social features and behavioral design.	Provides continuous adherence support and can personalize motivational framing over time.	Engagement does not necessarily imply clinical benefit; gamification may not sustain behavior change in all users.

3.3.1. AI-Personalized Exercise Prescription and Adaptive Training

One of the most promising applications of AI is the development of individualized exercise programs. Machine learning algorithms can integrate age, baseline fitness, previous activity history, personal goals, preferences, and time availability to generate tailored exercise prescriptions [70,71]. Compared with standardized recommendations, AI-based systems continuously adapt training to the user's evolving physiological and behavioral profile.

RL further extends this personalization by dynamically modifying exercise intensity, frequency, and progression according to individual responses [72–74]. Improvements in performance may trigger progressive overload, whereas fatigue, poor recovery, or declining adherence can lead to temporary reductions in training load or changes in exercise modality, promoting safer and more sustainable participation.

AI-based movement analysis also enables real-time technical feedback during unsupervised exercise. Applications such as ARFit use pose-estimation algorithms and augmented reality to compare user movements with reference models, providing immediate correction of posture and range of motion [75]. By improving exercise execution outside supervised settings, these systems may reduce injury risk while increasing confidence and adherence among inexperienced users.

3.3.2. Wearables and Physiological Monitoring

Wearable devices continuously collect physiological signals during daily activities, but their preventive value depends largely on AI algorithms capable of extracting clinically meaningful information. Time-series analysis of heart rate, heart rate variability (HRV), and accelerometry enables accurate estimation of exercise intensity and physiological adaptation.

Recent self-supervised learning models, such as Step2Heart [76], have demonstrated the ability to derive personalized physiological representations from multimodal wearable data without semantic labels. Trained on more than 280,000 h of sensor recordings, these models accurately predict heart rate from accelerometry alone while generating latent representations associated with BMI, VO_2max , age, sex, and energy expenditure. Such individualized physiological profiling may facilitate early detection of changes in fitness, recovery, and cardiometabolic health.

AI also supports recovery monitoring by integrating HRV, sleep quality, muscle soreness, stress, and performance trends [77,78]. Machine learning models have successfully predicted daily recovery status and HRV fluctuations in endurance athletes, with the most informative predictors differing substantially across individuals [79]. This supports personalized rather than standardized recovery assessment.

By integrating these data streams, AI systems can provide contextual recommendations such as reducing exercise intensity, scheduling active recovery, or modifying training sessions in response to physiological stress. Such adaptive feedback may help maintain regular physical activity while minimizing both inactivity and excessive training load.

3.3.3. Conversational AI and Behavioral Support

Behavioral adherence remains one of the major challenges in physical activity promotion. AI-powered conversational agents using natural language processing can deliver personalized coaching through natural dialogue while incorporating behavioral change techniques such as motivational interviewing [80–82]. Their principal contribution lies in providing continuous support between clinical or coaching encounters, when motivation often fluctuates.

AI systems can also implement adaptive behavioral nudges by identifying prolonged sedentary periods or recurring inactivity patterns and delivering context-specific prompts. Unlike fixed reminders, these interventions personalize timing and motivational framing according to previous user responses, daily routines, and individual preferences.

Gamification strategies further reinforce engagement through challenges, rewards, progression systems, and social interaction. Reinforcement learning approaches may optimize these motivational elements over time by identifying which strategies maximize adherence for each individual [83,84]. Although increased engagement alone does not

guarantee improved health outcomes, these behavioral support systems may facilitate the long-term maintenance of physically active lifestyles.

Collectively, these technologies illustrate the emergence of precision exercise medicine, in which AI integrates physiological, behavioral, and contextual information to personalize exercise prescription and sustain healthy movement behaviors. Their potential applications span cardiovascular, metabolic, obesity-related, and musculoskeletal prevention, although future research should determine whether these approaches translate into durable improvements in fitness, cardiometabolic health, and chronic disease incidence.

3.4. Mental Health

Mental health is increasingly recognized as a key component of primary prevention, given its close relationship with cardiovascular disease, metabolic disorders, sleep disturbances, and overall quality of life. AI is expanding access to preventive mental-health support through conversational agents, wearable sensing, and personalized digital interventions that can provide continuous assistance outside traditional clinical settings. Rather than replacing mental-health professionals, these technologies aim to facilitate early support, resilience building, and timely identification of individuals who may benefit from further evaluation. Table 4 summarizes the main AI-enabled approaches discussed in this section, highlighting their preventive value, limitations and variability across populations and implementation settings.

Table 4. Comparative summary of AI technologies for preventive mental-health support.

AI Method/Technology	Preventive Use and Performance Variability	Main Advantages	Main Limitations/Risks
Conversational agents for psychoeducation and self-management	Use natural-language interactions, mood check-ins and symptom self-reports to deliver CBT-informed support. Outcomes vary with symptom severity, perceived alliance and language quality.	Improves low-threshold access to support; may reduce stigma and encourage early help-seeking.	Not a substitute for psychotherapy; requires safeguards for crisis detection, hallucinations and inappropriate reassurance.
Immersive AI and VR-based therapeutic environments	Combine VR scenarios with AI dialogue for resilience-building or therapeutic exercises. Performance depends on immersion quality, usability and clinical oversight.	May increase engagement and allow experiential practice of coping strategies.	Evidence remains early; cost, cybersickness, access barriers and safety governance may limit scalability.
Digital biometrics for stress and emotional-state estimation	Analyze HR, HRV, activity, sleep and other physiological signals to infer stress. Accuracy varies with sensor quality, individual baseline, context and comorbidities.	Enables timely delivery of mindfulness, breathing or cognitive-reframing strategies.	Signals are non-specific and may reflect activity, illness or context rather than psychological distress.
Multimodal early-detection models for psychological vulnerability	Analyze language, sleep regularity, activity and social interaction to detect emerging distress. Utility depends on data completeness, consent and subgroup validation.	May identify risk earlier than episodic self-report and support timely referral.	High privacy burden; risk of false positives, demographic bias and inappropriate surveillance.

Table 4. *Cont.*

AI Method/Technology	Preventive Use and Performance Variability	Main Advantages	Main Limitations/Risks
Population-specific preventive applications	Adapt tools for students, workplaces and older adults. Effectiveness varies with organizational context, digital literacy, social support and long-term adoption.	Tailors prevention to life-stage and setting-specific needs, including stress management, loneliness reduction and cognitive/social engagement.	Generalizability is limited; workplace tools require strong governance to avoid surveillance or coercion.

3.4.1. AI-Based Conversational Agents and Immersive Digital Therapies

AI-powered conversational agents are transforming access to psychological support by providing immediate, low-threshold assistance without the delays often associated with traditional mental-health services. Platforms such as Wysa (Wysa Inc., Boston, MA, USA) employ natural language processing to deliver empathetic conversations based on evidence-supported approaches including cognitive behavioral therapy and motivational interviewing [85]. Studies suggest high user engagement and the development of perceived therapeutic alliances, indicating that conversational AI may encourage help-seeking and emotional self-management among individuals experiencing mild psychological distress.

AI-based chatbots may be particularly attractive for adolescents and young adults, who often perceive anonymous digital interactions as less stigmatizing than conventional mental-health care. Beyond emotional support, these systems can provide psychoeducation, coping strategies, and guidance toward professional care when needed.

Immersive platforms such as XAIA further extend these capabilities by combining virtual reality with large language model-based interaction to create more naturalistic therapeutic environments [86]. Although these technologies may improve engagement and accessibility, they should be regarded as supportive preventive tools rather than substitutes for clinician-delivered psychotherapy, particularly in individuals with severe psychiatric symptoms or complex clinical conditions.

3.4.2. AI-Enhanced Personalization and Early Detection of Psychological Distress

The integration of AI with wearable devices has transformed digital mental-health applications from generic wellness tools into personalized support systems. Physiological signals such as heart rate, blood pressure, oxygen saturation, and activity patterns can be analyzed to estimate psychophysiological stress and contextualize moment-to-moment emotional states [87–89]. Although these measures cannot diagnose mental disorders, they may provide useful indicators of evolving psychological strain. This information enables JITAI, in which AI delivers mindfulness exercises, breathing techniques, relaxation strategies, or cognitive reframing precisely when elevated stress is detected. Personalized delivery may increase intervention effectiveness by targeting periods of heightened vulnerability before stress contributes to sleep disruption, emotional dysregulation, or functional impairment.

AI can also analyze changes in written language, sleep regularity, physical activity, and social interaction that may signal emerging psychological vulnerability. BioBase (BioBeats Ltd., London, UK) exemplifies this approach by integrating wearable sensor data with AI-driven analytics to monitor stress and mood while providing personalized feedback and coping strategies [90]. Randomized studies in university students have reported reductions in anxiety and depressive symptoms together with improved mental well-being.

Nevertheless, these applications require careful attention to privacy, informed consent, false-positive findings, and appropriate escalation pathways when clinically significant symptoms emerge.

3.4.3. Population-Specific Preventive Applications

AI-based mental-health interventions can also be adapted to the needs of specific populations. Among students, digital platforms may provide psychoeducation, stress-management exercises, study-support strategies, and early recognition of psychological distress during periods of academic pressure and life transition [91,92].

In workplace settings, AI may assist in identifying workload patterns and organizational stressors while supporting employee well-being through personalized feedback and self-reflection tools [93,94]. However, workplace implementation requires robust governance to ensure transparency, informed consent, and protection against inappropriate surveillance.

For older adults, conversational agents, companion robots, and digital engagement platforms may reduce loneliness while supporting cognitive stimulation and social interaction [95,96]. Although evidence regarding long-term clinical outcomes remains limited, these approaches illustrate the flexibility of AI to personalize preventive mental-health strategies across different life stages and social contexts.

Overall, AI has the potential to strengthen preventive mental-health care by expanding access to early support, promoting adaptive coping strategies, and facilitating timely referral when symptoms exceed the scope of digital self-management. Realizing this potential will require rigorous evaluation of effectiveness together with careful attention to safety, privacy, equity, and integration with human clinical care.

4. Discussion

The evidence reviewed in this paper suggests that AI may substantially expand the scope and operational capacity of preventive medicine. Across nutrition, physical activity, sleep, and mental health, AI does not simply automate existing preventive strategies; it enables more continuous, personalized, and context-aware forms of support. Continuous physiological monitoring combined with ML-driven pattern recognition can improve individualized risk stratification beyond what is achievable with static population-level guidance alone. Adaptive feedback loops can intervene closer to the behavioral moment, rather than only during scheduled clinical encounters. Conversational agents and digital coaching systems may maintain supportive contact at a frequency and scale that would be difficult to achieve through human resources alone.

Taken together, these capabilities indicate that AI-augmented prevention is not a marginal extension of digital health, but a potentially important component of future proactive healthcare models. Its value lies in extending prevention into daily life, where risk behaviors occur, accumulate, and can still be modified. However, this potential should be interpreted with appropriate caution: the current evidence base supports improvements in monitoring, personalization, engagement, and selected behavioral or surrogate outcomes, but does not yet demonstrate broad reductions in long-term disease incidence or mortality.

4.1. Dynamic and Adaptive Preventive Systems

A cross-cutting finding emerging from the reviewed evidence is the potential advantage of dynamic, closed-loop systems over static recommendation engines. Studies implementing reinforcement learning or JITAI architectures suggest that interventions capable of adjusting timing, content, and intensity in response to user behavior may achieve better engagement and more relevant behavioral support than fixed or rule-based ap-

proaches. This pattern is observed across different domains, including exercise promotion, dietary adherence, sleep coaching, and mental-health support, and points to a domain-independent principle: prevention is more effective when the system can respond to the individual trajectory over time.

This has important implications for how AI-based preventive tools should be evaluated. Static performance metrics, such as dietary classification accuracy, sleep-stage detection, or risk-prediction AUC, remain necessary but are not sufficient. For primary prevention, the clinically relevant question is whether the system can learn from individual behavior, sustain engagement, support meaningful behavior change, and ultimately modify risk trajectories over time. In this sense, adaptive capacity should be considered a core feature of preventive AI, rather than a secondary technical refinement.

To consolidate these heterogeneous endpoints, Table 5 summarizes the main categories of evaluation metrics used across AI-supported preventive applications, with their advantages, limitations, and real-world applicability. These metrics should be interpreted as complementary, because no single metric is sufficient to demonstrate preventive effectiveness across physiological, behavioral, and clinical domains.

Table 5. Cross-cutting evaluation metrics for AI-supported preventive medicine.

Metric Category and Examples	Main Advantages	Main Limitations	Real-World Applicability in Preventive Medicine
Predictive-discrimination metrics (AUC, accuracy, sensitivity, specificity, F1 score)	Compare model classification performance and identify high-risk individuals.	May be affected by class imbalance; do not necessarily reflect calibration or clinical utility.	Useful for screening, early risk stratification and triage, but should be complemented by calibration and outcome measures.
Calibration and risk-estimation metrics (Brier score, calibration slope/intercept, predicted vs. observed risk)	Assess whether predicted risks correspond to observed outcomes and support individualized risk communication.	Require appropriate event rates and external validation; often underreported in short-term studies.	Important when AI tools are used to guide preventive decisions or personalized risk feedback.
Physiological signal validity and agreement metrics (MAE, RMSE, ICC, Bland-Altman agreement, epoch-level agreement)	Quantify agreement between wearable-derived or digital biomarker outputs and reference standards.	Performance may vary by device, sensor position, skin tone, age, movement artifacts and data completeness.	Essential for validating sleep, HRV, activity, glucose and recovery metrics before clinical interpretation.
Behavioral-change outcomes (steps/day, sedentary time, activity minutes, dietary adherence, sleep duration or efficiency)	Directly capture target behaviors and are sensitive to short-term intervention effects.	Often device- or self-report dependent; improvements may not translate into long-term clinical benefit.	Useful for monitoring adherence, behavior modification and early preventive response in real-world settings.
Engagement, adherence and usability metrics (retention, session frequency, completion rate, satisfaction, System Usability Scale)	Evaluate feasibility, acceptability and sustained interaction with digital interventions.	High engagement does not necessarily indicate improved health outcomes or equitable benefit.	Important for implementation studies and for identifying barriers to adoption in preventive care pathways.

Table 5. *Cont.*

Metric Category and Examples	Main Advantages	Main Limitations	Real-World Applicability in Preventive Medicine
Clinical and surrogate health outcomes (BMI, blood pressure, HbA1c, V02max, HRV, PHQ-9/GAD-7, sleep-quality scales)	Closer to clinically meaningful prevention than technical or engagement metrics alone.	Many remain surrogate endpoints and may require longer follow-up to demonstrate disease prevention.	Relevant for assessing whether AI-supported interventions modify cardiometabolic, psychological or sleep-related risk.
Longitudinal sustainability metrics (maintenance of behavior change, relapse rates, trajectory analyses, follow-up outcomes)	Capture durability of effects, which is central to primary prevention and healthspan-oriented care.	Require longer studies, repeated measurements and careful handling of attrition and missing data.	Useful for determining whether short-term digital engagement leads to sustained preventive benefit.
Equity, fairness and subgroup metrics (subgroup AUC/calibration, differential error rates, missingness patterns)	Identify whether model performance differs across demographic, socioeconomic or clinical subgroups.	Frequently underreported and limited by small or non-representative validation samples.	Necessary for responsible deployment and for preventing AI-enabled prevention from widening health inequities.

4.2. Integrated Multimodal Prevention

A second emergent pattern concerns the interdependence of lifestyle domains. Although most reviewed tools address a single domain in isolation, sleep, nutrition, physical activity, and psychological well-being are biologically and behaviorally interconnected. Sleep disruption may influence appetite regulation and glucose metabolism; chronic stress may reduce motivation for physical activity and impair sleep quality; and sedentary behavior may worsen cardiometabolic risk and contribute to poorer sleep and mental well-being. For this reason, single-domain AI tools may capture only part of an individual's preventive-risk profile.

The evidence reviewed here suggests that multimodal systems integrating data across several lifestyle domains may be better positioned to detect compound risk states. For example, the simultaneous worsening of glucose variability, HRV, sleep fragmentation, and activity patterns may indicate a more meaningful shift in health trajectory than any single abnormal parameter considered in isolation. This convergence toward holistic sensing is one of the most clinically relevant directions for preventive AI. However, the field still lacks robust evidence on integrated platforms capable of assessing and intervening across nutrition, physical activity, sleep, and mental health simultaneously. Bridging this gap should be considered a priority for future research and implementation.

4.3. Human Oversight and Explainable AI in Preventive Medicine

The clinical and public health implications of these developments are substantial, but they should be framed carefully. AI-based preventive tools are most defensibly positioned as adjuncts to, rather than replacements for, structured clinical preventive care. Their distinctive value lies in extending the reach of prevention into the intervals between clinical contacts, supporting autonomous behavior change, and identifying early warning signals that can be evaluated within an appropriate clinical framework. In this model, AI does not replace preventive medicine; it increases its continuity, personalization, and responsiveness [97–99]. The most plausible implementation pathway is an AI–human collaboration model, in which algorithms process continuous or repeated data streams, detect emerging risk patterns, and support personalized feedback, while clinicians provide

interpretation, prioritization, ethical judgment, and relational support. This division of roles is particularly important in primary prevention, where many signals are probabilistic, context-dependent, and not immediately pathological. Therefore, the goal should not be to automate preventive care entirely, but to create systems that help clinicians and individuals act earlier, more precisely, and with better longitudinal information.

Explainable AI (XAI) is important for the safe and meaningful implementation of AI-supported prevention, as these systems often generate probabilistic risk estimates or personalized recommendations from heterogeneous longitudinal data. Methods such as SHAP analysis, feature-importance ranking, counterfactual explanations, and transparent model reporting can support clinical interpretation, user trust, shared decision-making, and the identification of possible bias or model drift.

In primary prevention, XAI has specific practical relevance because AI outputs are often directed toward individuals without clinically manifest disease. In this context, interpretable models can support population risk stratification, clarify which modifiable factors contribute most to an individual's risk profile, and help clinicians distinguish actionable early-warning signals from non-specific physiological or behavioral variability. Explainable intervention plans are also important for implementation, because users and clinicians need to understand why a recommendation is proposed, which risk factor it targets, and how it should be adapted over time.

However, XAI should not be considered a stand-alone solution. Explainability can improve transparency, but it cannot by itself eliminate sensor-level bias, prevent LLM confabulation, ensure privacy protection, or replace external validation and regulatory oversight. Therefore, XAI should be integrated within a broader Responsible AI framework combining interpretability, fairness assessment, human supervision, post-deployment monitoring, and governance safeguards.

4.4. Current Limitations of the Evidence Base

Several limitations of the current evidence base warrant explicit acknowledgment. First, many studies are short-term and rely on surrogate, behavioral, or engagement outcomes rather than hard clinical endpoints such as incident cardiovascular disease, type 2 diabetes, major depressive disorder, cancer incidence, disability, or all-cause mortality. Long-term cohort studies and AI-based intervention trials assessing such endpoints remain scarce and heterogeneous. As a result, the evidence supporting a causal effect of AI-supported primary prevention on long-term disease incidence remains largely inferential, even when short-term improvements in monitoring, adherence, or risk-related behaviors are observed. Second, study populations are often self-selected, digitally literate, and recruited from high-income or highly resourced settings. This limits generalizability to populations with lower digital access, lower health literacy, multimorbidity, socioeconomic vulnerability, or higher baseline risk, who may in fact stand to benefit most from effective primary-prevention strategies.

Third, Responsible AI challenges remain insufficiently addressed. These include sensor-level bias, subgroup performance differences related to skin tone, age, sex, body composition, disability, device type, or data completeness, and LLM-related risks such as linguistic, cultural, or socioeconomic bias. Sensor-dependent AI applications are also constrained by hardware-level limitations, including sensor noise, motion artefacts, variable sampling frequency, limited signal resolution in flexible or consumer-grade wearables, and differences in device placement or adherence. These constraints may affect the reliability of physiological and behavioral features used for AI inference, particularly in free-living conditions where signals are less controlled than in laboratory settings. Therefore, fu-

ture studies should report device characteristics, signal-quality procedures, missing-data handling, and validation across different wearable platforms.

Finally, most available tools still address single lifestyle domains in isolation. This fragmentation limits the ability to evaluate additive or synergistic effects across nutrition, physical activity, sleep, and mental health, despite strong biological plausibility that integrated multimodal interventions may produce greater preventive benefit than domain-specific tools alone [100,101].

4.5. Future Research Directions

Future research should prioritize four directions:

First, long-term randomized studies are needed to determine whether AI-supported preventive interventions can produce durable improvements in clinically meaningful outcomes, not only short-term changes in engagement, behavior, or surrogate biomarkers. Whenever possible, these studies should include predefined hard endpoints, longitudinal follow-up, and subgroup analyses to assess differential effectiveness across age, sex, socioeconomic status, digital literacy, comorbidity, and baseline risk.

Second, the development and validation of integrated multimodal platforms should become a research priority. Rather than optimizing isolated tools for nutrition, physical activity, sleep, or mental health, future systems should evaluate how these domains interact and whether coordinated interventions across multiple behaviors can produce additive or synergistic preventive effects. Such platforms will require robust data integration, transparent modelling strategies, and clinically interpretable outputs that can support both individual self-management and professional decision-making.

Third, future research should promote open science practices, including the development of shared benchmarking datasets, transparent reporting of algorithmic pipelines, and, whenever possible, public availability of code. At present, many AI applications in preventive medicine rely on proprietary platforms, commercial wearable devices, or non-public datasets, limiting reproducibility and direct comparison across studies. Greater openness would improve methodological transparency, support external validation, and facilitate benchmarking across different preventive AI approaches.

Fourth, Responsible AI and regulatory governance frameworks must evolve to address AI-specific risks in preventive contexts. These include LLM confabulation, model drift, sensor-level bias, privacy risks from continuous behavioral monitoring, unclear accountability, and inappropriate escalation or reassurance. For AI-enabled prevention to be clinically credible, performance disclosure, external validation, human oversight, and post-market surveillance should be treated as implementation requirements rather than optional safeguards.

5. Conclusions

This review suggests that AI has moved beyond isolated proof-of-concept applications in primary prevention. Across nutrition, physical activity, sleep, and mental health, current evidence indicates that ML-driven personalization, continuous monitoring, and adaptive behavioral support can improve risk-relevant processes such as self-monitoring, engagement, adherence, early risk identification, and selected behavioral outcomes. The functional logic is coherent across domains: systems that can respond to individual trajectories over time appear better aligned with the needs of preventive medicine than static, one-size-fits-all recommendations. This convergence strengthens the rationale for AI-supported prevention as a promising component of future healthspan-oriented care.

What the current evidence does not yet support is the claim that AI-driven prevention reduces long-term disease burden at the population level. That question requires

larger studies, longer follow-up, and clinically meaningful endpoints that the field has not yet consistently produced. Realizing the potential of AI-supported prevention will therefore require three parallel commitments: generating robust long-term outcome evidence; addressing Responsible AI challenges, including equity, privacy, and accountability; and integrating AI tools into clinical and public-health workflows without weakening human oversight.

The trajectory of the field is clear: AI has the potential to change what preventive medicine can do, making it more continuous where it has traditionally been episodic, more personalized where it has often been generic, and more scalable where it has been constrained by limited human and organizational resources [102]. The central challenge is no longer whether AI can generate preventive insights, but whether these insights can be validated, governed, and implemented in ways that improve health without increasing inequity, overmedicalization, or loss of human judgment. If these conditions are met, AI-supported prevention may become an important component of a more proactive, healthspan-oriented model of care.

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