International Journal of Emerging Trends in Computer Science and Information Technology
ISSN: 3050-9246 | https://doi.org/10.63282/3050-9246.IJETCSIT-V7I3P102
Eureka Vision Publication | Volume 7, Issue 3, 10-20, 2026

Original Article

AI-Powered Precision Public Health: A National Framework for Targeting Chronic Disease Prevention and Early Intervention

Tan Tho Nguyen
Independent Researcher, USA.

Received On: 17/05/2026 Revised On: 14/06/2026 Accepted On: 24/06/2026 Published On: 06/07/2026

Abstract - Chronic diseases remain among the leading causes of preventable illness, disability, mortality, and healthcare expenditure in many national health systems. Traditional public health approaches have contributed significantly to disease prevention, but they often rely on broad population-level strategies, delayed surveillance, and reactive intervention models that may fail to identify high-risk individuals and communities early enough. This paper proposes an AI-powered precision public health framework for targeting chronic disease prevention and early intervention at national level. The framework integrates electronic health records, public health surveillance data, social determinants of health, genomic risk information, and predictive analytics to support earlier risk detection, population segmentation, and tailored prevention strategies. It emphasizes the use of artificial intelligence not as a replacement for public health expertise, but as a decision-support mechanism for improving resource allocation, screening, care coordination, and intervention timing. The paper also highlights the ethical, governance, and equity challenges associated with AI implementation, including algorithmic bias, privacy risks, data quality limitations, transparency, and public trust. It argues that AI-powered precision public health can strengthen chronic disease prevention when implemented through responsible governance, human oversight, equity-focused design, and continuous learning health systems. The proposed framework provides a national policy direction for improving early detection, reducing preventable complications, and promoting more targeted and equitable health outcomes.

Keywords - Artificial Intelligence; Precision Public Health; Chronic Disease Prevention; Predictive Analytics; Early Intervention; Health Equity; National Health Policy.

1. Introduction and Background

1.1. National Burden of Chronic Diseases

Chronic diseases are a challenge for national health systems. Cardiovascular disease, diabetes, obesity, hypertension, cancer, chronic respiratory illness, and chronic kidney disease contribute to premature mortality, disability, reduced quality of life, and greater pressure on healthcare services. Preventable complications increase hospital admissions, long-term care needs, and public expenditure, while illness-related absence and reduced functional capacity undermine workforce productivity.

These conditions usually develop gradually. Their progression reflects behavioural factors, including diet, physical inactivity, tobacco use, and alcohol consumption; clinical factors such as elevated blood pressure, glucose, and cholesterol; genetic susceptibility; environmental exposures; and socioeconomic circumstances. Limited access to nutritious food, safe housing, education, transport, stable employment, and primary care can increase risk and reduce prevention opportunities. National systems must therefore identify rising risk before serious complications emerge, rather than focus mainly on late-stage treatment.

1.2. Limitations of Traditional Public Health Prevention

Traditional prevention commonly relies on health education campaigns, periodic screening, risk-factor messaging, and routine primary-care services. These measures remain essential because they raise awareness, support healthier choices, and reach large populations. However, broad interventions do not always distinguish people with rapidly increasing risk from those with lower immediate need. Screening at fixed intervals may overlook changes between visits, particularly for people who face barriers to care or use preventive services inconsistently.

Rose (2001) argued that prevention must address both high-risk individuals and the wider distribution of risk in populations. Focusing only on people already classified as high risk overlooks the cumulative burden created by common, moderate-risk exposures. Conversely, universal programmes alone may not direct intensive support to people likely to develop near-term complications. Precision public health complements population prevention by using information to identify emerging risk, prioritise outreach, and direct resources fairly to individuals and communities with the greatest preventive need.

1.3. Emergence of Precision Public Health and AI

Precision public health uses timely, high-quality, and granular information to deliver the right intervention to the right population at the right time. It is related to, but distinct from, precision medicine. Precision medicine focuses primarily on diagnosis and treatment for individual patients using clinical, biological, and genetic information. Precision public health applies comparable data-driven principles to prevention, surveillance, programme planning, resource allocation, and health equity. The approaches are complementary: individual risk insights can inform public action, while population data can reveal disease patterns, inequalities, and unmet need.

Electronic health records, laboratory systems, disease registries, claims data, wearable technologies, and social determinants data have expanded the basis for this approach. Dolley (2018) identified big data as a resource for precision public health, while Dowell et al. (2016) emphasised applying data to target interventions effectively. Khoury et al. (2015) argued that precision public health can extend the benefits of precision medicine to broader populations. AI and predictive analytics can support this goal by detecting risk patterns, estimating future disease likelihood, and identifying groups that may benefit from earlier support. Ginsburg and Phillips (2018) noted that precision innovation must demonstrate value, a necessary consideration for investment in AI-enabled prevention.

1.4. Problem Statement

Despite these opportunities, chronic disease prevention systems are constrained by fragmented data, weak interoperability between health and social care services, delayed risk detection, and unequal access to screening and preventive support. Clinical records may be separated across institutions, while social, environmental, and community-level information is often absent from routine risk assessment. This limits the capacity to identify vulnerable populations promptly, coordinate prevention, and allocate resources according to changing needs.

AI may help overcome these gaps, but it can also worsen inequality when models are trained on incomplete, biased, or historically unequal data. Gianfrancesco et al. (2018) warned that electronic health record data can embed important sources of bias. Obermeyer et al. (2019) showed how using healthcare cost as a proxy for health need can produce racial bias, while Vyas et al. (2020) cautioned against uncritical race-based algorithmic adjustments. Norori et al. (2021) therefore stressed transparency, open science, and equity-oriented governance. Any national AI framework must treat data quality, fairness, privacy, explainability, and human oversight as requirements.

1.5. Aim and Objectives

The aim of this paper is to develop an AI-powered national precision public health framework for improving chronic disease prevention and early intervention. Its objectives are to examine the role of AI and health data in risk prediction; identify data sources needed for national precision public health; propose a framework for risk stratification and targeted prevention; address equity, ethics, governance, and implementation; and identify evaluation indicators, future research priorities, and policy implications.

2. Literature and Conceptual Foundations

2.1. Precision Public Health, Population Health, and Prevention

Precision public health provides a useful foundation for rethinking national chronic disease prevention because it connects traditional population health goals with more refined methods of risk identification and intervention planning. Unlike approaches that treat the population as a single uniform group, precision public health uses more detailed data to identify which individuals, communities, and geographic areas are most exposed to preventable disease risks. Its aim is not to replace broad public health action, but to strengthen it by improving the timing, reach, and relevance of prevention.

Rose’s distinction between “sick individuals” and “sick populations” remains central to this discussion. Rose (2001) argued that a person’s individual risk must be understood within the wider distribution of risk across the population. This means that chronic disease prevention cannot depend only on treating people who already show clinical symptoms. It must also reduce risk across the wider population while giving additional attention to those most likely to develop complications. Precision public health builds on this logic by combining universal prevention with targeted support for high-risk groups. Khoury et al. (2015) argued that the era of precision medicine should also strengthen public health by improving population-level prevention, surveillance, and intervention targeting. Similarly, Dowell et al. (2016) emphasized that precision public health depends on better data, better analytics, and better delivery of timely interventions. In this sense, AI-powered precision public health can help national systems move from delayed response to earlier and more proactive prevention.

2.2. Social Determinants of Health and Chronic Disease Inequality

Chronic disease risk cannot be explained only by biological, genetic, or clinical factors. Conditions such as diabetes, hypertension, cardiovascular disease, obesity, and chronic kidney disease are strongly shaped by the environments in which people are born, grow, work, live, and age. Income affects access to healthy food, stable housing, transport, and preventive care. Education influences health literacy, employment opportunities, and the ability to act on health information. Housing quality, neighborhood safety, air pollution, food access, and healthcare availability also affect long-term disease risk.

Braveman and Gottlieb (2014) described social determinants as the “causes of the causes,” meaning that poor health outcomes often arise from deeper social and economic conditions rather than individual choices alone. This perspective is important for AI-powered public health because prediction models that focus only on clinical records may fail to identify the structural conditions that produce chronic disease inequality. Marmot et al. (2008) further argued that reducing health inequality requires action on the social gradient in health, not only treatment after disease occurs. Therefore, a national precision public health framework must include social determinants of health as part of risk assessment, programme design, and equity monitoring. Without this, AI may identify risk but fail to address the conditions that produce it.

2.3. Big Data, Electronic Health Records, and Public Health Surveillance

Big data has created new opportunities for more responsive chronic disease prevention. Electronic health records, claims data, registries, laboratory systems, pharmacy records, wearable devices, genomic information, and social determinants datasets can help public health agencies detect risk earlier and plan interventions more effectively. Birkhead et al. (2015) noted that electronic health records can support public health surveillance by providing timely information on disease patterns, clinical outcomes, and service use. Casey et al. (2016) also showed that electronic health records are valuable for population health research because they allow researchers and policymakers to examine risk patterns across large groups.

Analytics can also help identify patients who are both high-risk and high-cost. Bates et al. (2014) argued that healthcare data can be used to identify patients who may benefit from earlier care management and targeted intervention. Dolley (2018) similarly emphasized that big data is central to precision public health because it enables more specific understanding of who is at risk, where risks are concentrated, and which interventions may be most effective. However, big data must be interpreted carefully because incomplete records, unequal access to care, and biased data collection may distort risk estimates.

Table 1. Core Data Sources for AI-Powered Precision Public Health

Data source	Examples	Prevention value
Electronic health records	Diagnoses, medication, laboratory results	Identifies clinical risk patterns
Claims data	Service use, cost, referrals	Detects high-risk and high-cost groups
Public health registries	Screening and disease records	Supports surveillance and planning
Social determinants data	Income, housing, food access	Guides equity-focused intervention
Genomic data	Family history, inherited risk	Supports personalized prevention
Wearable data	Activity, sleep, heart rate	Enables continuous risk monitoring

2.4. AI, Machine Learning, and Chronic Disease Prediction

Artificial intelligence and machine learning can strengthen chronic disease prevention by identifying complex patterns that may not be visible through traditional statistical methods. Machine learning can support classification, risk prediction, clustering, natural language processing, and image-based analysis. Beam and Kohane (2018) argued that machine learning is becoming increasingly important in healthcare because of its ability to learn from large and complex datasets. Miotto et al. (2018) and Esteva et al. (2019) also showed that deep learning can improve pattern recognition across clinical data, images, and health records, although careful validation remains necessary. Topol (2019) emphasized that AI should support human judgment rather than replace clinical and public health expertise.

Several chronic disease applications illustrate this potential. Ahlqvist et al. (2018) used data-driven clustering to identify subgroups of adult-onset diabetes with different risks and outcomes. Hippisley-Cox et al. (2008) and Weng et al. (2017) demonstrated the value of routine clinical data for cardiovascular risk prediction. Khera et al. (2016) showed that genetic risk and healthy lifestyle interact in coronary disease prevention. Krittanawong et al. (2017) and Rumsfeld et al. (2016) discussed AI and big-data analytics in cardiovascular medicine, while Poplin et al. (2018) showed that retinal fundus images could be used to predict cardiovascular risk factors through deep learning. Together, these studies show that AI can improve prevention when prediction is linked to timely, equitable, and clinically meaningful intervention.

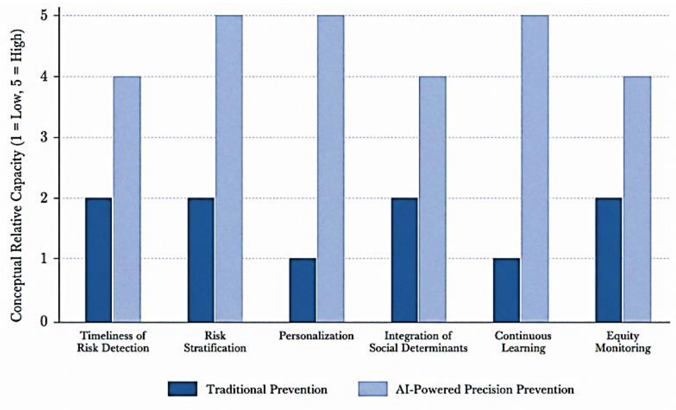

Figure 1. Traditional Prevention versus AI-Powered Precision Prevention

3. Methodological Approach and Framework Development

3.1. Study Design

This paper adopts a conceptual and policy-oriented framework design to examine how artificial intelligence can strengthen national chronic disease prevention and early intervention. It does not report a clinical trial, retrospective patient-level analysis, or original primary data. Instead, it synthesises evidence from precision public health, population health, health informatics, predictive modelling, health equity, and AI governance to develop a national framework.

This design is appropriate because AI-enabled prevention depends on more than algorithmic accuracy. It also requires an understanding of population need, data availability, prevention pathways, public trust, and institutional safeguards. Precision public health uses timely, granular information to direct prevention towards populations most likely to benefit while improving health across the population (Khoury et al., 2015; Dowell et al., 2016). AI is therefore treated as a decision-support capability that can improve risk identification, prevention targeting, and outcome monitoring, rather than replace clinical judgement, public health expertise, or community action.

The framework is developed through a structured narrative synthesis. It considers which chronic disease risks should be identified, which data sources can support risk assessment, how models should be validated, how predictions should lead to action, and which safeguards are needed to prevent bias and inequity. It should be locally adapted and empirically validated before influencing service delivery or resource allocation.

3.2. Framework Development Domains

The framework is built around six interconnected domains. First, population health and chronic disease prevention establish its purpose. National prevention should combine universal health promotion with additional support for people and communities with greater need. This reflects Rose’s (2001) argument that prevention must address both high-risk individuals and the wider distribution of risk.

Second, precision public health guides risk stratification and intervention targeting. Preventive support should be matched to need, from universal education and screening reminders for lower-risk groups to intensive follow-up for people with multiple clinical and social vulnerabilities. This is consistent with Dowell et al. (2016), who stress identifying priority populations, matching interventions to need, delivering them efficiently, and evaluating outcomes.

Third, AI and machine-learning applications provide the capacity to detect patterns in large datasets. Models may support earlier identification of cardiovascular risk, diabetes progression, uncontrolled hypertension, chronic kidney disease, and avoidable hospital admission. Their value depends on whether predictions are linked to screening, lifestyle support, care coordination, and referral.

Fourth, electronic health records and big-data infrastructure provide the operational base. Linked EHRs, laboratory records, pharmacy data, claims data, disease registries, and surveillance systems support risk profiles and monitoring. Their use requires interoperability, common standards, secure access controls, and processes for identifying missing or under-recorded information.

Fifth, social determinants of health and health equity are central design requirements. Data on housing, income, education, food access, geography, and service availability can show why risk accumulates in particular communities. Including these indicators helps ensure that resources respond to need rather than only patterns of healthcare use (Braveman & Gottlieb, 2014; Marmot et al., 2008).

Finally, ethical governance, transparency, and accountability guide responsible implementation. The learning health system perspective connects routine data, intervention outcomes, and continuing improvement. Friedman et al. (2015) describe such systems as generating and applying knowledge within routine practice. Kelly et al. (2019) likewise emphasise that AI should show meaningful clinical and public health value, not merely technical promise.

3.3. Prediction Model Development and Reporting Requirements

AI models should be developed through transparent, reproducible, and ethically sound procedures. Developers should assess completeness, accuracy, consistency, timeliness, and representativeness before model training. EHR data may contain missing values, selective documentation, and historical inequalities in access to care, each of which can distort risk predictions (Gianfrancesco et al., 2018).

Training data should be diverse, and models should be tested across geographical areas, demographic groups, and care settings. Internal validation alone is insufficient for national use. External validation is needed to determine whether a model performs consistently beyond the population in which it was developed. Assessment should include discrimination, calibration, and practical utility. Discrimination indicates how effectively a model separates higher-risk from lower-risk people, whereas calibration assesses whether predicted probabilities correspond to observed outcomes (Steyerberg et al., 2010).

Transparent reporting is equally necessary. The TRIPOD statement guides reporting of data sources, participant selection, predictors, outcomes, missing-data handling, performance measures, and limitations (Collins et al., 2015). National implementation should also include fairness audits, model-drift monitoring, escalation procedures, and human professional review. Char et al. (2018) note that ethical AI requires accountability for decisions affecting outreach, referral, and resource allocation. These safeguards help ensure that AI supports equitable prevention rather than reproducing disparities.

Table 2. Requirements for Developing and Evaluating AI Risk Prediction Models

Requirement	National Expectation	Suggested Measure
Data quality	Complete, accurate, timely records	Missingness and consistency checks
Representativeness	Coverage of population groups and regions	Subgroup and geographic coverage
Validation	Testing beyond development data	External validation performance
Performance	Accurate, reliable risk estimation	Discrimination and calibration
Fairness	Comparable performance across groups	Subgroup error-rate audit
Monitoring	Detection of post-deployment change	Model-drift review and recalibration

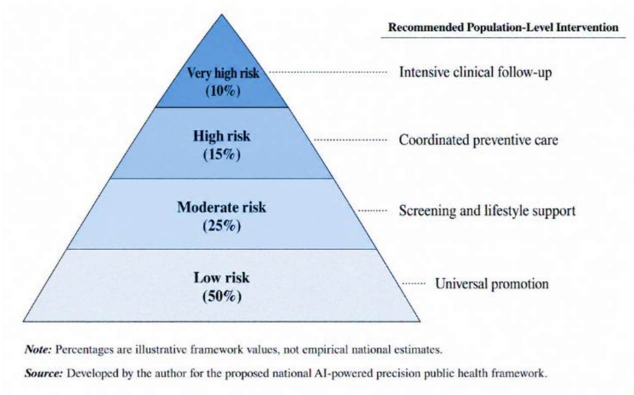

Figure 2. Illustrative National Chronic Disease Risk Stratification Pyramid

4. Proposed National AI-Powered Precision Public Health Framework

4.1. Framework Overview

The proposed national AI-powered precision public health framework is designed to strengthen chronic disease prevention and early intervention through coordinated use of health data, predictive intelligence, targeted services, and continuous evaluation. It should be understood as a national public health strategy rather than a standalone technology platform. Its purpose is to enable health authorities, primary-care providers, and community organisations to identify emerging risks earlier, allocate prevention resources more effectively, and reduce avoidable complications from chronic diseases.

The framework consists of six connected layers: national data integration; AI-powered risk intelligence; population segmentation and priority setting; targeted prevention and early intervention; equity, ethics, and governance; and learning health system feedback. These layers operate as an integrated cycle. Data collected across health and social systems are transformed into actionable risk insights, which guide preventive interventions and are subsequently evaluated to improve future decisions. AI therefore functions as a decision-support mechanism that complements professional judgment, public health expertise, and primary-care capacity rather than replacing them.

At national level, the framework can support prevention of cardiovascular disease, diabetes, hypertension, obesity, chronic kidney disease, and multimorbidity. It can also improve the identification of communities experiencing poor screening uptake, limited access to care, or elevated social vulnerability. The central principle is that prevention services should be delivered according to risk, need, and accessibility, while maintaining universal health promotion for the broader population.

4.2. National Data Integration Layer

The first layer involves the secure integration of multiple health and population data sources. A national precision public health system should connect electronic health records, insurance claims, disease registries, laboratory information systems, pharmacy records, screening data, hospital admissions, mortality records, and public health surveillance databases. Where legally and ethically appropriate, this information can be supplemented with social determinants of health data, including housing conditions, education, income, food access, geographic deprivation, and transport barriers.

Electronic health records are particularly valuable because they contain longitudinal clinical information, including diagnoses, medications, laboratory values, vital signs, referrals, and treatment history. Their use in public health surveillance can strengthen the timely detection of disease patterns and gaps in preventive care (Birkhead et al., 2015). Similarly, population health research using electronic health records can help identify disease burden, care inequalities, and service-use patterns across different demographic groups (Casey et al., 2016). Linked data systems also support the identification of patients with complex needs, high service use, and elevated risk of preventable complications (Bates et al., 2014).

However, data integration must be supported by interoperability standards, common data definitions, secure data-sharing agreements, privacy protections, and clear institutional accountability. Health data should be collected and used only for legitimate public health purposes, with strong safeguards against unauthorised access, discrimination, or misuse. Standardisation is essential because inconsistent coding, incomplete records, and missing demographic information may reduce the accuracy and fairness of AI predictions.

4.3. AI-Powered Risk Intelligence Layer

The second layer uses artificial intelligence and predictive analytics to identify individuals and communities at elevated risk of chronic disease or preventable deterioration. AI models can analyse large and complex datasets to detect patterns that may be difficult to identify through traditional methods alone. These models should support earlier prevention, not merely predict illness after substantial harm has already occurred.

For cardiovascular disease, established risk tools such as QRISK2 demonstrate the value of combining routine clinical variables to estimate future risk and guide preventive care (Hippisley-Cox et al., 2008). Machine-learning approaches may further improve cardiovascular prediction by recognising complex interactions among demographic, clinical, behavioural, and laboratory variables (Weng et al., 2017). AI has also shown increasing potential in precision cardiovascular medicine, particularly for risk classification, imaging analysis, and personalised treatment planning (Krittanawong et al., 2017; Rumsfeld et al., 2016).

Risk intelligence can also improve diabetes prevention and management. Ahlqvist et al. (2018) demonstrated that adult-onset diabetes can be divided into clinically meaningful subgroups with different disease trajectories and complication risks. This suggests that prevention and follow-up strategies can be more effective when they move beyond a single broad diagnostic category. Genetic information may also be useful where appropriate, as coronary disease risk is influenced by both inherited susceptibility and lifestyle behaviours (Khera et al., 2016). In addition, deep-learning approaches have shown that retinal images can reveal cardiovascular risk factors, illustrating the growing capacity of AI to extract preventive information from non-traditional clinical data sources (Poplin et al., 2018).

At community level, AI can map areas with low screening participation, poor medication adherence, limited primary-care access, or high rates of preventable hospital admissions. These insights can help public health agencies direct outreach services and prevention investments toward communities with the greatest unmet need.

4.4. Population Segmentation and Targeted Intervention Layer

Risk prediction is valuable only when it leads to practical, proportionate, and accessible action. The third and fourth layers of the framework therefore translate AI-generated insights into population segmentation and targeted prevention pathways. Individuals and communities can be grouped according to their predicted risk, clinical profile, social vulnerability, and likelihood of benefiting from early intervention.

Low-risk populations may receive universal health education, routine screening reminders, and digital health information. Moderate-risk groups may benefit from personalised lifestyle guidance, nutrition support, physical-activity programmes, smoking cessation services, or follow-up screening. High-risk individuals may require coordinated primary-care support, medication review, community health-worker outreach, or referral to specialist services. Very high-risk patients, particularly those with multiple chronic conditions or predicted near-term complications, may require intensive monitoring and multidisciplinary intervention.

Table 3. AI-Supported Chronic Disease Prevention Pathways

Risk Category	AI-Identified Indicators	Recommended Prevention Response
Low risk	No major clinical or social risk indicators	Universal health promotion and routine screening reminders
Moderate risk	Early metabolic risks, family history, unhealthy lifestyle indicators	Digital coaching, nutrition advice, lifestyle support, repeat screening
High risk	Multiple risk factors, poor disease control, missed appointments	Primary-care referral, care coordination, medication review
Very high risk	Predicted complications, multimorbidity, severe social vulnerability	Intensive follow-up, specialist referral, multidisciplinary care
High-risk community	Geographic clustering of disease, deprivation, and poor screening uptake	Mobile screening, community outreach, local prevention programmes

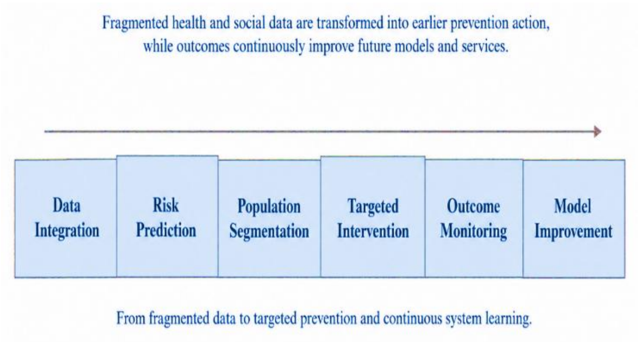

Figure 3. AI-Enabled Chronic Disease Prevention Continuum

4.5. Learning Health System Feedback Layer

The final layer ensures that the national framework remains responsive rather than static. A learning health system continuously uses information generated during routine care and prevention activities to improve policies, service delivery, and population outcomes. Friedman et al. (2015) argue that learning health systems depend on the systematic use of data, evidence, and feedback to support ongoing improvement.

Within this framework, intervention outcomes such as screening uptake, early diagnosis rates, treatment adherence, hospital admissions, complications, and patient-reported outcomes should be monitored over time. These findings should then be used to assess whether AI predictions are accurate, whether interventions are reaching priority groups, and whether unequal outcomes are emerging. Models may need recalibration when population characteristics, care practices, or disease patterns change.

Continuous feedback is particularly important for equity. A model that performs well overall may still produce weaker predictions for underserved populations. Routine monitoring can identify such disparities and support corrective action. In this way, the learning health system layer ensures that AI-powered precision public health remains transparent, adaptive, accountable, and focused on improving prevention outcomes for the entire population.

5. Governance, Equity, Implementation, and Evaluation

5.1. Equity-Centred Design

Equity must be embedded from the beginning of data selection, model development, intervention planning, and performance monitoring. Chronic disease burden and preventable complications are not distributed evenly. Risks are often concentrated among people affected by poverty, insecure housing, food insecurity, inadequate primary-care access, discrimination, transport barriers, low health literacy, and geographic isolation. A national AI system that relies only on laboratory results, body mass index, blood pressure, and recorded diagnoses may detect clinical risk while overlooking the conditions that shape disease prevention and care access.

The framework should therefore combine clinical and behavioural information with carefully governed social determinants of health data. Relevant measures may include area deprivation, food access, housing quality, employment insecurity, travel time to healthcare, digital connectivity, and local screening availability. These variables should never be used to stigmatise communities. Their purpose is to identify where additional resources and tailored preventive services are required. Braveman and Gottlieb (2014) argue that public health must address the social causes underlying health outcomes, while Marmot et al. (2008) show that health equity depends on coordinated action across health, social, and economic policy.

Equity-centred design also requires meaningful community involvement. Communities should help define acceptable data uses, priority needs, communication approaches, and intervention pathways. AI predictions must lead to accessible support, including mobile screening, culturally appropriate education, outreach, nutrition support, and navigation to primary care. Monitoring should examine whether risk identification and subsequent services are distributed fairly across socioeconomic, geographic, demographic, and digitally excluded groups.

5.2. Ethical Risks and Algorithmic Bias

AI can support prevention only when ethical risks are managed throughout data collection, development, deployment, and evaluation. Unequal data representation is a major concern. People with limited healthcare access may have incomplete electronic health records, while data from well-served populations can dominate training datasets. Gianfrancesco et al. (2018) explain that EHR-based machine-learning models may inherit bias from missingness, clinical documentation, diagnostic variation, and unequal healthcare use. Consequently, a model may appear accurate overall yet produce unreliable results for underrepresented groups.

Outcome labels can also be unfair. Obermeyer et al. (2019) showed that an algorithm using cost as a proxy for health need underestimated the needs of Black patients because lower expenditure did not necessarily reflect lower illness burden. National models should therefore use outcomes that directly measure health need, preventable harm, and access to effective care. Vyas et al. (2020) likewise caution that race correction can reproduce historical inequities when race is used as a simplistic biological proxy.

Governance should require documentation of data sources, model objectives, variables, validation findings, and known limitations. Subgroup audits should assess calibration, false-positive and false-negative rates, and service access across age, sex, ethnicity, income, disability, and geography. Norori et al. (2021) identify transparency and open science as important mechanisms for bias detection and mitigation. Privacy safeguards, secure access controls, independent oversight, and accountability procedures are equally necessary. AI recommendations must remain decision-support tools that clinicians and public health professionals can review, challenge, and override.

5.3. National Implementation Strategy

Implementation should progress through evidence-based phases rather than immediate nationwide deployment. First, national authorities should establish data-governance rules, interoperability standards, cybersecurity safeguards, and accountability arrangements. Second, chronic disease infrastructure should be strengthened by linking electronic health records, laboratory records, screening systems, surveillance data, pharmacy information, and appropriate social determinants datasets. Third, models should be trained and validated using representative data, with assessment of discrimination, calibration, clinical usefulness, and equity.

Validated tools should then be piloted in selected regions, primary-care networks, or high-burden communities. Pilots should assess feasibility, workforce readiness, patient experience, privacy concerns, referral completion, and whether AI-supported outreach produces timely preventive action. Kelly et al. (2019) stress that real-world impact depends on workflow integration, not predictive performance alone. Topol (2019) similarly highlights the complementary roles of human expertise and AI, while Char et al. (2018) emphasise the need for ethical oversight when algorithms influence service access. Following successful pilots, national scaling should include workforce training, technical assistance, shared standards, and continuous monitoring. In line with the learning health system model, intervention outcomes should inform ongoing model and policy refinement (Friedman et al., 2015).

Table 4. National Implementation and Evaluation Roadmap

Phase	Core Action	Indicator
Governance	Set privacy and interoperability rules	Framework approved
Infrastructure	Link priority datasets	Data completeness
Model development	Train and validate models	Accuracy, calibration, fairness
Pilot	Test in selected settings	Uptake and referral completion
Equity review	Audit subgroup outcomes	Error-rate gaps
Scale-up	Expand validated tools	Population coverage
Learning cycle	Update models from outcomes	Fewer preventable complications

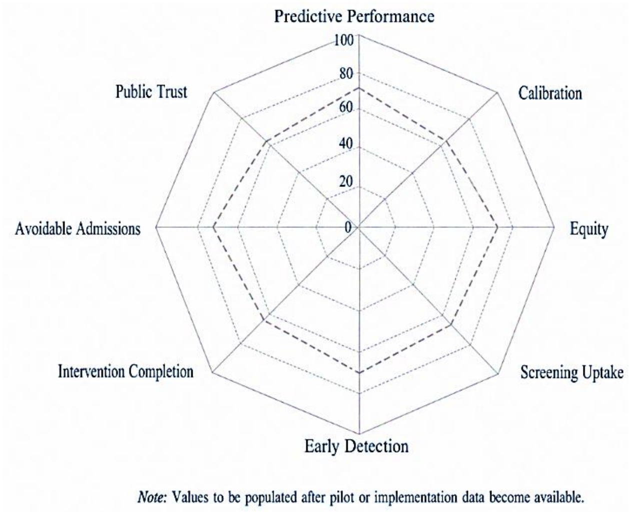

Figure 4. National Evaluation Dashboard for AI-Powered Precision Public Health

6. Discussion

6.1. Interpretation of the Proposed Framework

The proposed framework positions AI-powered precision public health as a tool for strengthening chronic disease prevention, rather than replacing established public health practice. Its central premise is that national health systems can shift from reactive models, where intervention follows diagnosis, complication, or hospital admission, towards earlier identification of modifiable risk and timely prevention. By linking electronic health records, public health surveillance, behavioural indicators, and social determinants of health, AI can show who is at risk, where risk is concentrated, and which response may be most appropriate.

The contribution of AI is therefore not limited to producing risk scores. It can connect fragmented information, detect patterns that routine analysis may miss, and translate insights into action. Predictive models may identify people with emerging cardiometabolic risk, patients likely to miss preventive follow-up, or communities where limited screening access coincides with deprivation. Public health agencies can then prioritise outreach, screening, lifestyle support, primary-care referral, and care coordination before avoidable complications emerge.

Targeted prevention must, however, remain compatible with population-wide health improvement. Rose (2001) showed that a substantial burden of disease arises from the many people at moderate risk, rather than only from a small high-risk group. The framework therefore supports a dual strategy: universal policies that improve health across the population, alongside additional support for people and communities facing greater risk. AI can help refine resource allocation without reducing prevention to a narrowly individualised approach. Precision public health should consequently be seen as an enhancement of population health practice.

6.2. Contribution to Public Health Policy and Practice

The framework contributes to national policy by showing how AI can support decisions throughout the prevention continuum. Beyond disease prediction, AI can inform programme planning, geographic targeting, equity monitoring, resource allocation, service forecasting, and early-warning systems. National and regional agencies could identify places where screening rates are low, chronic disease risk is increasing, or preventive services do not reach people with the greatest need. This can improve outreach and resource use.

AI should not, however, be treated as an independent technological solution. Its impact depends on whether predictions lead to accessible and effective interventions. A risk model has limited value if primary-care services cannot accept referrals, prevention programmes are under-resourced, or people lack transport, internet access, health literacy, or trust in the health system. Topol (2019) argued that AI creates most value when computational capacity is combined with human expertise. Likewise, Kelly et al. (2019) stressed the importance of clinical relevance, workflow integration, and real-world benefit. The framework therefore requires investment in workforce capability, interoperable data systems, public engagement, and responsive prevention services.

Data on intervention uptake, outcomes, service use, and model performance should continuously guide future decisions (Friedman et al., 2015). This feedback loop enables health systems to recalibrate models, identify implementation gaps, and adapt preventive strategies as population needs change.

6.3. Ethical and Equity Implications

Ethical governance and equity must be foundational requirements rather than secondary safeguards. AI models can reproduce structural inequities when their training data reflect unequal access to care, incomplete documentation, or historically biased decisions. Char et al. (2018) identified accountability, transparency, and patient protection as central challenges in healthcare machine learning. Obermeyer et al. (2019) demonstrated how an algorithm that used health expenditure as a proxy for need underestimated the needs of Black patients because spending reflected unequal access to care rather than illness burden.

National precision public health systems must therefore be evaluated across demographic, geographic, and socioeconomic groups before and during deployment. Race-based adjustments require particular caution because race is a social and political category, not a biological shortcut for risk assessment (Vyas et al., 2020). Transparent documentation, independent validation, recurring bias audits, public reporting of model performance, and clear procedures for correction are necessary. Open science and inclusive data governance can strengthen fairness and accountability (Norori et al., 2021). Community participation is equally important because populations affected by AI-supported decisions should help shape data use and intervention delivery.

6.4. Limitations

This paper is conceptual and framework-based. It does not test the proposed framework using original national datasets, prospective intervention trials, or real-world cost-effectiveness analyses. It should therefore be interpreted as a policy and research guide rather than evidence of immediate effectiveness. Its applicability may also differ across countries because health systems vary in data maturity, legal requirements, financing, workforce capacity, and digital inclusion.

Additional limitations include incomplete data capture, weak interoperability between health and social-care systems, possible algorithmic bias, privacy concerns, and model drift as populations and care practices change. Finally, accurate prediction alone does not improve outcomes. Preventive benefit depends on whether identified people can access timely, affordable, acceptable behavioural, clinical, and social support. Empirical studies are needed to test the framework's feasibility, fairness, effectiveness, and sustainability in diverse national settings.

7. Future Research and Conclusion

7.1. Future Research Directions

Future research should move beyond conceptual discussion and empirically test the proposed AI-powered precision public health framework using real-world national, regional, and community-level datasets. Although artificial intelligence offers considerable potential for improving chronic disease prevention and early intervention, its value must be demonstrated through robust evidence across diverse population groups, health systems, and implementation environments.

A first priority is the validation of AI models using diverse electronic health record, public health surveillance, claims, laboratory, and social determinants of health datasets. Models developed in a single healthcare setting may perform poorly when applied to populations with different demographic profiles, disease patterns, data quality, or access to care. Therefore, external validation across multiple regions and healthcare systems is necessary to determine whether risk-prediction models are reliable, transferable, and clinically useful. Transparent reporting should follow recognised principles such as the TRIPOD framework, which promotes clarity in the development, validation, and reporting of multivariable prediction models (Collins et al., 2015).

Future studies should also compare AI-based approaches with established risk-scoring tools and conventional statistical models. Traditional models such as QRISK2 have demonstrated the practical value of structured cardiovascular risk prediction in routine care (Hippisley-Cox et al., 2008). However, AI may identify more complex nonlinear relationships among clinical, behavioural, genetic, and social variables. Comparative studies should therefore examine whether machine-learning models provide meaningful improvements in discrimination, calibration, clinical decision-making, and prevention outcomes beyond existing tools. Such evaluations should not rely solely on accuracy measures. Model calibration, net benefit, sensitivity, specificity, and real-world utility should be assessed comprehensively, consistent with the prediction-model evaluation principles described by Steyerberg et al. (2010).

Longitudinal research is also required to establish whether AI-supported early intervention reduces chronic disease complications over time. Future studies should assess whether risk stratification followed by timely screening, lifestyle support, medication management, primary-care referral, and community outreach can reduce preventable hospital admissions, late diagnoses, cardiovascular events, diabetes complications, and other adverse outcomes. Importantly, these studies should investigate whether earlier identification of risk translates into better health outcomes rather than simply producing more predictions.

Equity-focused research must remain central to future investigation. AI systems should be evaluated across age, sex, ethnicity, income level, geographic location, disability status, and other social characteristics that influence healthcare access and chronic disease burden. Research has shown that health algorithms can produce unfair results when they are trained on biased data or rely on inappropriate proxy measures for health need (Obermeyer et al., 2019). Future studies should therefore include routine fairness audits, subgroup performance analysis, and clear mechanisms for identifying and correcting unequal model outcomes. Open and transparent approaches to bias detection are particularly important for ensuring that AI strengthens, rather than undermines, health equity (Norori et al., 2021).

Further research should examine the cost-effectiveness of national AI-powered prevention systems. Governments need evidence on whether investment in data infrastructure, AI development, workforce training, and prevention programmes produces measurable savings through reduced hospitalisation, improved disease control, and earlier intervention. Studies should also investigate privacy-preserving data-sharing approaches, including federated learning, secure data linkage, and governance models that allow useful analysis without exposing sensitive personal information.

Finally, implementation research should explore public trust, informed consent, community engagement, workforce readiness, workflow integration, and scalability. AI tools are unlikely to achieve meaningful impact when they are introduced without adequate training, stakeholder involvement, or alignment with existing public health and primary-care processes. The learning health system model provides a useful foundation because it supports continuous feedback, adaptation, and improvement through the routine use of data and evidence (Friedman et al., 2015). As Kelly et al. (2019) observed, successful AI deployment depends not only on technical capability but also on its ability to generate practical and sustained impact within real healthcare settings.

7.2. Conclusion

Chronic disease prevention requires a national transition from fragmented, delayed, and reactive systems toward prevention models that are predictive, targeted, equitable, and continuously responsive to changing population needs. AI-powered precision public health provides an important opportunity to support this transition by integrating clinical, behavioural, social, and population-level information to identify risk earlier and guide more relevant interventions.

However, AI should not be viewed as a replacement for public health institutions, clinical expertise, or community-based prevention. Its effectiveness depends on high-quality and representative data, transparent model development, responsible governance, equity-centred design, public trust, and meaningful human oversight. When implemented responsibly, a national precision public health framework can help governments direct prevention resources more effectively, reduce avoidable chronic disease complications, and improve health outcomes across diverse populations.

References

[1] Dolley, S. (2018). Big data's role in precision public health. Frontiers in public health, 6, 68.

[2] Rose, G. (2001). Sick individuals and sick populations. International journal of epidemiology, 30(3), 427-432.

[3] Ginsburg, G. S., & Phillips, K. A. (2018). Precision medicine: from science to value. Health affairs, 37(5), 694-701.

[4] Dowell, S. F., Blazes, D., & Desmond-Hellmann, S. (2016). Four steps to precision public health. Nature, 540(7632), 189-191.

[5] Ahlqvist, E., Storm, P., Käräjämäki, A., Martinell, M., Dorkhan, M., Carlsson, A., ... & Groop, L. (2018). Novel subgroups of adult-onset diabetes and their association with outcomes: a data-driven cluster analysis of six variables. The lancet Diabetes & endocrinology, 6(5), 361-369.

[6] Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: using analytics to identify and manage high-risk and high-cost patients. Health affairs, 33(7), 1123-1131.

[7] Beam, A. L., & Kohane, I. S. (2018). Big data and machine learning in health care. Jama, 319(13), 1317-1318.

[8] Birkhead, G. S., Klompas, M., & Shah, N. R. (2015). Uses of electronic health records for public health surveillance to advance public health. Annual review of public health, 36(1), 345-359.

[9] Braveman, P., & Gottlieb, L. (2014). The social determinants of health: it's time to consider the causes of the causes. Public health reports, 129(1_suppl2), 19-31.

[10] Casey, J. A., Schwartz, B. S., Stewart, W. F., & Adler, N. E. (2016). Using electronic health records for population health research: a review of methods and applications. Annual review of public health, 37(1), 61-81.

[11] Char, D. S., Shah, N. H., & Magnus, D. (2018). Implementing machine learning in health care—addressing ethical challenges. The New England journal of medicine, 378(11), 981.

[12] Collins, G. S., Reitsma, J. B., Altman, D. G., & Moons, K. G. (2015). Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement. Journal of British Surgery, 102(3), 148-158.

[13] Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. Nature medicine, 25(1), 24-29.

[14] Friedman, C., Rubin, J., Brown, J., Buntin, M., Corn, M., Etheredge, L., ... & Van Houweling, D. (2015). Toward a science of learning systems: a research agenda for the high-functioning Learning Health System. Journal of the American Medical Informatics Association, 22(1), 43-50.

[15] Gianfrancesco, M. A., Tamang, S., Yazdany, J., & Schmajuk, G. (2018). Potential biases in machine learning algorithms using electronic health record data. JAMA internal medicine, 178(11), 1544-1547.

[16] Hippisley-Cox, J., Coupland, C., Vinogradova, Y., Robson, J., Minhas, R., Sheikh, A., & Brindle, P. (2008). Predicting cardiovascular risk in England and Wales: prospective derivation and validation of QRISK2. Bmj, 336(7659), 1475-1482.

[17] Khera, A. V., Emdin, C. A., Drake, I., Natarajan, P., Bick, A. G., Cook, N. R., ... & Kathiresan, S. (2016). Genetic risk, adherence to a healthy lifestyle, and coronary disease. New England Journal of Medicine, 375(24), 2349-2358.

[18] Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. BMC medicine, 17(1), 195.

[19] Khoury, M. J., Iademarco, M. F., & Riley, W. T. (2015). Precision public health for the era of precision medicine. American journal of preventive medicine, 50(3), 398.

[20] Krittanawong, C., Zhang, H., Wang, Z., Aydar, M., & Kitai, T. (2017). Artificial intelligence in precision cardiovascular medicine. Journal of the American College of Cardiology, 69(21), 2657-2664.

[21] Marmot, M., Friel, S., Bell, R., Houweling, T. A., & Taylor, S. (2008). Closing the gap in a generation: health equity through action on the social determinants of health. The lancet, 372(9650), 1661-1669.

[22] Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare: review, opportunities and challenges. Briefings in bioinformatics, 19(6), 1236-1246.

[23] Norori, N., Hu, Q., Aellen, F. M., Faraci, F. D., & Tzovara, A. (2021). Addressing bias in big data and AI for health care: A call for open science. Patterns, 2(10).

[24] Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447-453.

[25] Poplin, R., Varadarajan, A. V., Blumer, K., Liu, Y., McConnell, M. V., Corrado, G. S., ... & Webster, D. R. (2018). Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. Nature biomedical engineering, 2(3), 158-164.

[26] Rumsfeld, J. S., Joynt, K. E., & Maddox, T. M. (2016). Big data analytics to improve cardiovascular care: promise and challenges. Nature Reviews Cardiology, 13(6), 350-359.

[27] Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T., Gonen, M., Obuchowski, N., ... & Kattan, M. W. (2010). Assessing the performance of prediction models: a framework for traditional and novel measures. Epidemiology, 21(1), 128-138.

[28] Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. Nature medicine, 25(1), 44-56.

[29] Vyas, D. A., Eisenstein, L. G., & Jones, D. S. (2020). Hidden in plain sight—reconsidering the use of race correction in clinical algorithms. New England Journal of Medicine, 383(9), 874-882.

[30] Weng, S. F., Reps, J., Kai, J., Garibaldi, J. M., & Qureshi, N. (2017). Can machine-learning improve cardiovascular risk prediction using routine clinical data?. PloS one, 12(4), e0174944.