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Artificial Intelligence – Enabled Integration of Physical Fitness Monitoring and Public Fitness Promotion: Mechanisms, Opportunities, and Governance Challenges

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Abstract： As public health governance shifts from a disease-treatment paradigm toward health promotion and risk prevention, physical health monitoring has become a foundational component of population health management. In practice, however, monitoring systems remain constrained by a "monitoring-heavy, translation-light" dilemma, in which monitoring outputs fail to translate effectively into risk assessment and intervention, resulting in a structural break in the monitoring–assessment–intervention chain. Using a mechanisms–opportunities–governance challenges analytical framework, this paper synthesizes how artificial intelligence (AI) enables the integration of physical health monitoring with public health promotion and delineates the key conditions shaping its effectiveness. We argue that AI facilitates integration through multi-source health data integration and population profiling, population-level risk identification and prediction, and an intelligent feedback loop linking continuous monitoring, stratified intervention, outcome evaluation, and iterative adjustment. These mechanisms support a shift from periodic, static monitoring to stratified and dynamic population-level health promotion. At the same time, AI creates opportunities to enhance governance responsiveness, optimize public resource allocation, and strengthen evidence generation for policy design and evaluation, while also introducing governance challenges related to data privacy and ethics, algorithmic bias, health inequities, and accountability. We conclude that AI should be positioned as a tool and

infrastructure within public health governance rather than an autonomous decision-maker, and that its real-world impact ultimately depends on institutional design, data governance, accountability, and human–AI collaboration.

Keywords: artificial intelligence; physical health monitoring; public health promotion; precision public health; governance challenge

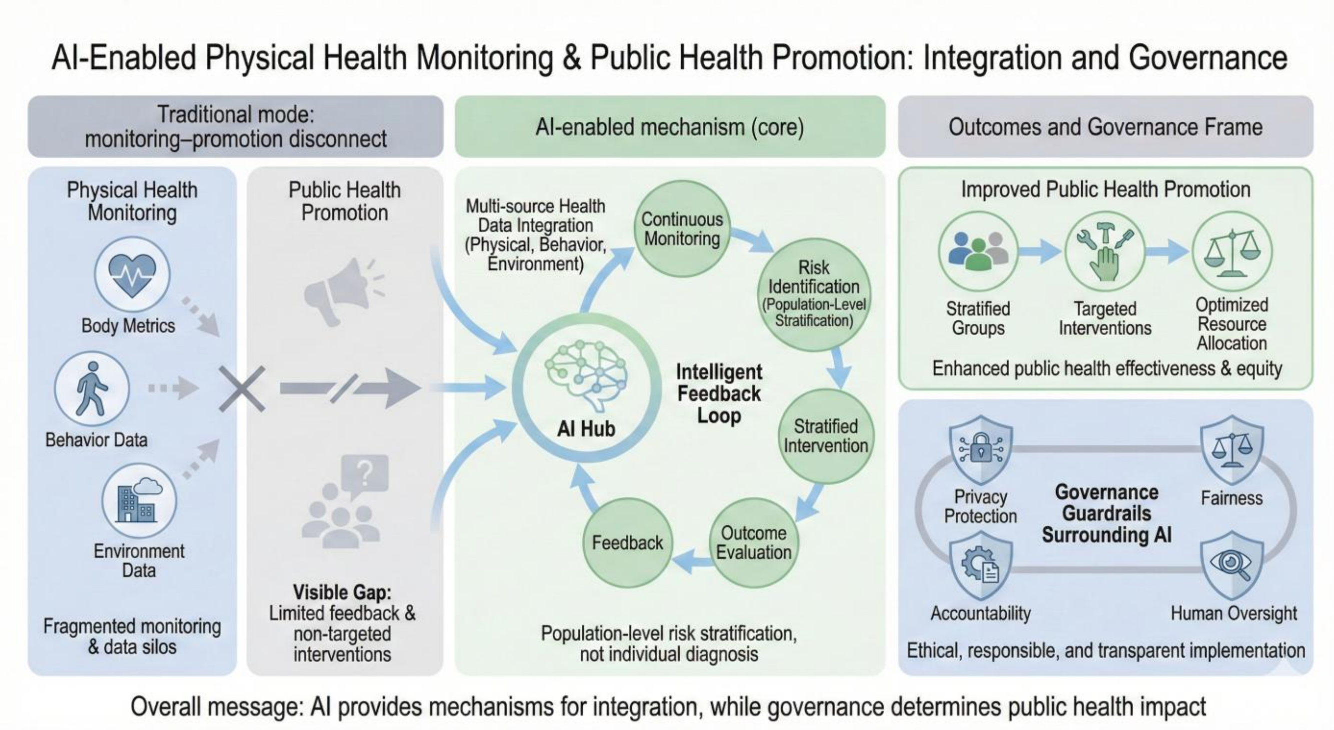

Figure 1. AI-enabled integration of physical health monitoring and public health promotion

This figure illustrates a conceptual framework showing how artificial intelligence (AI) facilitates the integration of physical health monitoring and public health promotion. Traditional approaches are characterized by fragmented monitoring and a disconnect between data collection and health promotion actions. In contrast, the AI-enabled mechanism integrates multi-source health data within an AI hub and establishes an intelligent feedback loop involving continuous monitoring, population-level risk identification, stratified interventions, outcome evaluation, and iterative feedback. The framework emphasizes population risk stratification rather than individual diagnosis, and highlights key public health outcomes alongside essential governance guardrails, including privacy protection, fairness, accountability, and human oversight.

Introduction

As public health governance has progressively shifted from a disease-treatment–centered paradigm toward one emphasizing health promotion and risk prevention, physical health monitoring has assumed an increasingly foundational role within public health systems[1]. Over time, physical fitness monitoring, behavioral surveillance, and health screening have provided essential data for understanding population health status and have served as critical informational foundations for health promotion[2]. Nevertheless, in practice, a persistent "monitoring-heavy, translation-light" dilemma remains: monitoring outputs often fail to be effectively integrated into subsequent assessment and intervention processes, resulting in a structural breakdown in the "monitoring–assessment–intervention" chain and a pronounced disconnect between data accumulation and health promotion outcomes. Prior research within public health surveillance frameworks has explicitly emphasized that "monitoring must lead to action" and has identified a closed-loop process of monitoring, decision-making, and intervention as a key mechanism underlying public health performance[3]. Concurrently, the emergence of "precision public health," oriented toward population stratification and risk identification[4], has driven a shift from "average-based interventions" to data-driven risk stratification and optimized resource allocation, while underscoring the population-level application of big data and machine learning/artificial intelligence (AI) to enable prediction, stratification, and strategy optimization[4,5].

In recent years, the rapid development of AI technologies in the field of public health has provided a new practical foundation for addressing the aforementioned "monitoring–action" disconnection. On the one hand, digital health strategies and the informatization of public health emphasize the integration and governance of multi-source health data, making cross-context data aggregation, interoperability, and continuous monitoring possible[6]. On the other hand, the advantages of AI in pattern recognition, predictive analysis, and decision support enable health monitoring results to be translated into more targeted and dynamic health promotion strategies, thereby achieving health risk identification, population stratification, and intervention priority ranking at the population level[7]. Against this background, AI has gradually become an important technological pivot for promoting the integration of physical health monitoring and public health promotion: by constructing operational mechanisms centered on data integration, risk identification, and intelligent feedback, it facilitates the effective translation of monitoring information into assessment and intervention decisions[6]. At the same time, the introduction of AI has also brought new application opportunities such as enhanced precision, improved efficiency, and evidence-based decision-making; however, the ethical and governance challenges it raises in areas such as data privacy protection, algorithmic bias, technological governance capacity, and boundaries of responsibility cannot be overlooked[8,9]. Therefore, it is necessary to systematically examine and critically explore the integration of AI–enabled physical health monitoring and public health promotion from a comprehensive perspective encompassing mechanisms, opportunities, and governance challenges, and to enhance the publicness, credibility, and fairness of technological applications by embedding data principles, privacy protection, and accountability mechanisms at the governance level[10].

1. Traditional models of physical health monitoring and public health promotion and their limitations

1.1. Functional positioning and empirical forms of physical health monitoring

Within traditional public health governance frameworks, physical health monitoring has primarily been positioned as a tool for the objective recording and aggregate description of population health status. Its core purpose is to capture the physical characteristics and health levels of specific populations at a given time point through standardized and systematic data collection. Whether focusing on fitness indicators through physical fitness monitoring or on physiological parameters and lifestyle behaviors through broader health monitoring, these approaches fundamentally aim to measure and present the "current state" of population health[3]. By aggregating and analyzing sample-level data, monitoring systems generate foundational statistical evidence to inform public health decision-making, allowing macro-level health disparities, structural patterns, and temporal trends to be identified and described[1].

From an operational perspective, traditional physical health monitoring is typically characterized by periodic implementation, static assessment, and a strong orientation toward end results. Monitoring activities are commonly conducted on an annual or phase-based basis, with emphasis placed on data collection and report generation at predefined time points, as well as on task completion and indicator compliance[6]. Within this framework, health monitoring is often conceptualized as an "assessment tool" or a "management instrument," with its primary value lying in the summarization and comparison of existing health conditions rather than in the continuous tracking of dynamic health changes. Although this results-oriented monitoring model partially satisfies the demand of public health management for statistical information and performance evaluation, it has also contributed to the practical institutionalization of physical health monitoring as a "terminal activity," thereby limiting its natural progression into subsequent intervention and health promotion processes.

1.2. Practical logic of public health promotion

Corresponding to physical health monitoring, traditional public health promotion practices mainly revolve around pathways such as health education, behavioral intervention, and environmental support. Their goal is to promote overall health improvement by enhancing individual cognition, guiding healthy behaviors, and optimizing living and social environments[2]. Within this practical logic, health education is regarded as a fundamental means of changing health behaviors, improving public health awareness through information dissemination and knowledge popularization; behavioral interventions focus on correcting unhealthy lifestyles and guiding individuals to form relatively stable healthy behavior patterns; while environmental support emphasizes providing sustainable external conditions for health behaviors through improvements in institutional, community, and physical environments[11].

However, in actual operation, public health promotion measures often rely more on existing experience, general guidelines, or macro-level judgment for their design and implementation, resulting in relatively limited targeting and dynamic adjustment capacity. On the one hand, intervention populations are mostly classified using broad criteria such as age, gender, or region, making it difficult to fully reflect differences among individuals or subgroups in health risks, behavioral patterns, and physiological characteristics; on the other hand, evaluations of health promotion effects often lag behind intervention implementation and lack real-time or continuous data feedback mechanisms[12]. Under such circumstances, public health promotion practices and physical health monitoring have not formed a close linkage, and monitoring data are difficult to translate into strong support for the precise formulation and dynamic optimization of intervention strategies, leaving health promotion to a certain extent still operating within an “experience-driven” implementation model.

1.3. Structural causes of the “monitoring–promotion” disconnect

From a systemic perspective, the disconnect between physical health monitoring and public health promotion does not stem from the failure of any single link, but rather arises from the interaction of multiple institutional arrangements and operational mechanisms. At the level of data utilization, traditional health monitoring remains largely confined to descriptive analysis, with its primary function focused on depicting current health conditions and population-level differences, while deeper analyses oriented toward decision support and intervention design remain insufficient[4]. As a result, substantial volumes of monitoring data are not effectively translated into inputs for risk assessment, intervention prioritization, or resource allocation, leaving the decision-making potential of data in public health governance largely unrealized.

Coarse modes of population stratification further intensify the disconnect between monitoring and promotion. In traditional practice, population classification relies predominantly on static demographic indicators, which limits the ability to capture the dynamic evolution of health risks and to identify heterogeneous responses among individuals exposed to identical interventions[5]. This "average-based" population perspective hinders the direct alignment of monitoring outputs with precision-oriented health promotion strategies, thereby weakening the practical relevance of monitoring information for guiding interventions.

The lack of feedback mechanisms represents another critical structural constraint preventing the formation of a closed-loop relationship between "monitoring" and "promotion." Monitoring results are often archived once reports are completed, with little sustained interaction with intervention implementation processes, and the outcomes of health promotion are seldom used to retroactively adjust monitoring priorities or indicator frameworks. Moreover, public health governance typically involves multiple actors—including health, sports, education, and community sectors—whose responsibilities are fragmented, and limited data sharing across governance domains further magnifies the structural divide between monitoring and action.

In sum, within traditional public health governance models, although physical health monitoring provides an essential informational foundation for understanding population health, structural constraints—including limited levels of data utilization, coarse population stratification, the absence of feedback mechanisms, and fragmented governance arrangements—impede the effective translation of monitoring outputs into sustained and precision-oriented public health promotion actions. These limitations highlight the need for new technological tools and governance approaches and establish a clear problem context for examining the role of AI in integrating health monitoring with health promotion.

2. Mechanisms through which AI enables the integration of physical health monitoring and public health promotion

2.1. Integration of multi-source health data and population profiling

A primary mechanism through which AI facilitates the integration of physical health monitoring and public health promotion lies in its capacity to integrate multi-source health data and to construct population-level health profiles. In contrast to traditional health monitoring, which relies largely on single or limited indicators, contemporary public health contexts are characterized by highly heterogeneous health data sources. These include indicators of physical functioning—such as physical fitness, body composition, and physiological measures—derived from physical health monitoring; behavioral data capturing lifestyles, exercise patterns, and health-related behaviors; and environmental exposure information encompassing air quality, the built environment, and socioeconomic conditions[13]. The coexistence of these diverse data sources implies that health risks are no longer attributable to isolated factors, but instead emerge from the interactive effects of biological, behavioral, and environmental determinants.

Within this process, AI does not merely "add more data," but instead enables the structured integration and relational modeling of heterogeneous datasets through machine learning, data fusion, and feature extraction techniques[14]. By applying AI algorithms, data originating from different sources and operating at different scales can be analyzed within a unified analytical framework, thereby overcoming the fragmentation and informational silos that characterize traditional monitoring systems. Importantly, this form of integration is not oriented toward individual-level diagnosis, but toward population-level pattern recognition, allowing public health governance to identify subgroups that share similar health characteristics, risk exposures, or behavioral patterns.

Population profiling thus represents a key outcome of multi-source health data integration. Through the automated learning and combination of health-related features, AI transforms populations from "statistical aggregates" into "collections of groups with differentiated health characteristics," providing a critical foundation for subsequent risk identification and stratified intervention design[14]. Notably, such profiles are not static labels; rather, they evolve dynamically as monitoring data are continuously updated, enabling public health decision-making to be adjusted in accordance with progressively refined representations of population health structures.

2.2. AI-based health risk identification and prediction

Building on the integration of multi-source health data, AI further drives a shift in public health governance from "post hoc evaluation" toward proactive risk early warning. Traditional physical health monitoring has largely relied on retrospective analyses, with its primary function centered on describing past health conditions or observed outcomes of change. By contrast, AI enables health monitoring to acquire forward-looking risk identification capabilities through pattern learning and predictive modeling[15]. At the core of this transformation is the expansion of health monitoring from merely "recording problems that have already occurred" to actively "identifying risks that may emerge."

At the population level, AI can identify high-risk groups and anticipate health trends by leveraging historical monitoring data in combination with contemporaneous exposure information. For instance, through the integrated analysis of physical fitness trajectories, the stability of behavioral patterns, and the cumulative effects of environmental risk exposures, algorithms can detect subgroups whose health risks are increasing at a faster pace or who exhibit heightened sensitivity to specific interventions[16].

Unlike individual-level diagnosis in clinical medicine, such risk identification does not aim to determine the presence of particular diseases; rather, it seeks to characterize changes in the probability and distribution of adverse health outcomes within defined populations over a specified future period.

Accordingly, AI-based health risk identification functions fundamentally as a population-oriented predictive instrument for public health governance. Its primary objective is to inform resource allocation, intervention prioritization, and the design of health promotion strategies, rather than to substitute for professional medical diagnosis[17]. This distinction is essential for preventing the over-medicalization of public health and for ensuring that AI applications in health promotion remain aligned with the legitimate scope of public governance and population-level management.

2.3. Intelligent feedback mechanisms linking physical health monitoring and health promotion

Building on multi-source data integration and risk identification, a central mechanism through which AI enables the integration of health monitoring and health promotion lies in the construction of an "intelligent feedback loop." Unlike traditional linear workflows, this loop emphasizes sustained interaction among monitoring, analysis, intervention, and evaluation, and represents the core mechanism through which genuine integration is achieved. Specifically, the intelligent feedback loop begins with continuous health monitoring and applies AI algorithms to newly generated data for real-time or near–real-time analysis, thereby dynamically detecting shifts in population health risk patterns [18].

On the basis of identified risk profiles, AI further supports the alignment and adaptive adjustment of health promotion strategies. By linking population profiles with accumulated evidence on intervention effectiveness, systems can recommend more targeted population-level health promotion measures, including differentiated exercise interventions, behavioral guidance, and environmental support strategies. Importantly, this process does not entail fully automated decision-making; rather, it functions as an evidence-based decision support mechanism for public health administrators, enabling intervention design to be iteratively optimized in response to real-time data[19].

Crucially, the evaluation of intervention outcomes does not mark the end of this process, but instead feeds back into subsequent monitoring and analytical stages. Through continuous learning from intervention response data, AI updates risk models and population profiles, thereby generating a dynamic cycle of "monitoring–identification–intervention–evaluation–re-monitoring"[20]. In this respect, the intelligent feedback loop serves as the operational hub of the integration between physical health monitoring and public health promotion, transforming monitoring data into "living data" that actively inform and drive sustained health improvement rather than remaining as static archives.

2.4. From population monitoring to stratified health promotion

AI does not propel public health toward "individual-level medicalization"; rather, its central value lies in enabling a structural transformation of population health governance. By integrating multi-source data and applying risk identification techniques, public health governance can move beyond uniform interventions directed at an "average population" toward stratified and group-specific health promotion strategies[21]. This shift does not privilege individual differences in isolation, but instead focuses on identifying subpopulations that share similar health risks and intervention needs at the population scale.

Within this framework, populations can be stratified into multiple tiers based on risk profiles, behavioral characteristics, or environmental exposure conditions, allowing differentiated health promotion interventions to be appropriately matched. Low-risk groups may prioritize health maintenance and risk prevention, whereas high-risk groups can be provided with more intensive and targeted support. In this context, AI functions as a structural and instrumental tool, enhancing the rational allocation of public health resources and improving efficiency, rather than substituting for professional judgment [22].

The integration of physical health monitoring and public health promotion thus culminates in an emerging public health model characterized by stratified governance. Through its systematic embedding within monitoring, analytical, and feedback processes, AI enables health promotion to transition from experience-driven practices to data-driven approaches, achieving alignment between precision and sustainability while maintaining the fundamental public health orientation.

3. Practical opportunities for AI-enabled public health promotion

3.1. Enhancing the responsiveness of public health governance

Within traditional public health governance models, the interval between the identification of health problems and the implementation of interventions is often prolonged by extensive processes of data aggregation, analysis, and decision-making. As a result, health risks may have already escalated or become entrenched by the time formal responses are initiated. The introduction of AI creates new practical opportunities to narrow the temporal gap between "problem identification" and "intervention response." Through automated analysis and continuous updating of health monitoring data, AI enables the earlier detection of population-level health risk signals, thereby shifting public health governance from reactive management toward anticipatory response[23].

Gains in responsiveness are reflected not only in the earlier identification of risks but also in the overall acceleration of governance processes. By automating data processing and pattern recognition, AI reduces dependence on manual statistical compilation and retrospective aggregation, allowing public health administrators to rapidly grasp emerging trends in population health and to initiate appropriate health promotion or intervention measures in a timely manner[24]

At the same time, AI offers robust technical support for optimizing public resource allocation. Under conditions of resource scarcity, public health governance faces persistent challenges in distributing resources effectively across diverse populations and health issues. By analyzing the spatial and temporal distribution of health risks and their trajectories, AI facilitates the identification of population groups and geographic areas with more urgent intervention needs, thereby enabling public health resources to be directed toward domains characterized by higher risk and greater potential returns[25]. This data-driven approach to resource allocation enhances the overall efficiency of health promotion investments and provides public health governance with decision-making processes that are more transparent and interpretable.

3.2. Advancing precision and dynamism in health promotion strategies

Another key opportunity associated with AI-enabled public health promotion lies in facilitating a transition from uniformly designed interventions to precision-oriented implementation. Traditional health promotion strategies are often developed on the basis of generic guidelines or average population characteristics, limiting their capacity to adequately address heterogeneity across populations in health risks, behavioral patterns, and social environments. By enabling population stratification and the identification of risk profiles, AI allows health promotion strategies to be differentially aligned with population needs at the group level[26].

Within this framework, populations exhibiting distinct risk levels or behavioral characteristics can be assigned to tailored intervention pathways, thereby reducing the resource inefficiencies and uneven outcomes associated with “one-size-fits-all” approaches to health promotion. Importantly, AI also supports the dynamic adjustment of health promotion strategies. As health monitoring data are continuously updated, intervention effectiveness and population responses can be assessed in real time or near–real time, enabling health promotion programs to be iteratively refined and adapted in response to data-driven feedback[27]. This dynamic capacity transforms health promotion from a discrete, one-off activity into a sustained and adaptive governance process.

It is important to emphasize that such precision and dynamism do not signify a shift toward individualized medicalization within public health. Rather, they represent an approach to achieving a "more appropriate allocation of interventions" through population stratification. In this context, AI serves a structural regulatory function by enhancing the alignment between health promotion strategies and population needs while preserving the equity and broad coverage that define public health practice[28]. Through this mechanism, the overall effectiveness and sustainability of health promotion efforts can be substantially strengthened.

3.3. Supporting evidence-based public health decision-making

Evidence-based decision-making constitutes a foundational principle of modern public health governance, and AI offers novel technical capacities to strengthen evidence-based public health decisions. By integrating multi-source health data and enabling systematic analysis, AI can provide policymakers with more comprehensive, timely, and granular empirical evidence, thereby facilitating a gradual shift in public health decision-making from experience-driven judgment toward data-driven approaches[29]. During the policy design phase, AI contributes to the identification of critical health risk factors and their underlying pathways, offering a robust scientific basis for the development of targeted health promotion policies.

AI also plays a pivotal role during policy implementation and evaluation. Through the continuous monitoring and analysis of health data collected before and after interventions, AI supports systematic assessments of the effectiveness of health promotion measures and reveals heterogeneous responses to policy interventions across different population groups[30]. Such real-world data–based evaluation approaches help overcome key limitations of traditional assessments, including restricted sample sizes and delayed feedback, thereby enabling policy adjustments that are both timelier and more precise.

From a macro-level perspective, the application of AI is driving a transformation in public health decision-making systems from "static evaluation" toward "learning-oriented governance." Policies are no longer conceived as one-off designs implemented unchanged over extended periods; instead, they are increasingly understood as dynamic processes that evolve through continuous data feedback and outcome evaluation[31]. In this respect, AI functions not only as a technical instrument but also as a critical catalyst for updating public health governance paradigms and decision-making logics.

4. Governance challenges and potential risks

4.1. Health data privacy and ethical risks

AI–enabled public health promotion depends heavily on the continuous collection, integration, and analysis of multi-source health data, rendering data privacy and ethical risks unavoidable governance concerns. Unlike general informational data, health data are inherently sensitive, encompassing not only individuals' physical conditions, behavioral patterns, and living environments, but also potentially revealing socioeconomic status, disease susceptibility, and other forms of vulnerability[32]. Within public health contexts, the misuse or leakage of such data can generate consequences that extend beyond the individual level, increasing the risk of group labeling and social discrimination.

From an ethical perspective, informed consent mechanisms face renewed challenges. Traditional public health monitoring typically occurs within clearly defined survey or medical examination settings, where individuals possess relatively clear understandings of the purposes and uses of data collection. By contrast, in AI-supported environments characterized by continuous monitoring and secondary data use, health data may be repeatedly repurposed for diverse analytical objectives, many of which may not be foreseeable at the point of initial data collection[33]. As a result, "one-time informed consent" becomes insufficient to encompass the full range of data uses across the data life cycle, raising critical questions regarding the validity of consent and the ethical legitimacy of such practices.

Moreover, the increasing ambiguity surrounding the boundaries of health data use further exacerbates governance risks. As public health data intersect with datasets held by commercial platforms, technology firms, or other institutional actors, the purposes of data utilization may gradually drift away from the original objectives of health promotion[34]. In the absence of clearly articulated data governance frameworks and accountability arrangements, AI applications may inadvertently erode public trust in public health governance, thereby weakening the social acceptance and legitimacy of health promotion interventions.

4.2. Algorithmic bias and health inequalities

Beyond concerns related to privacy and ethics, algorithmic bias and the health inequalities it generates represent a central challenge in the application of AI within public health. The performance of AI models is highly contingent on the quality and representativeness of training data; however, real-world health datasets are often shaped by sampling practices, monitoring coverage, and underlying social structures, limiting their capacity to adequately capture the health conditions of all population groups [35]. When certain populations are systematically underrepresented or absent from the data, algorithmic outputs related to risk identification and intervention recommendations may disproportionately disadvantage these groups.

At the public health level, such biases tend to be amplified rather than attenuated. On the one hand, AI systems are more likely to detect risks and allocate services to populations with abundant data and frequent monitoring, while paying insufficient attention to marginalized groups, individuals of lower socioeconomic status, or those with limited digital access. On the other hand, decision-support systems built on biased datasets may unintentionally reinforce existing patterns of health inequality. For instance, intervention resources may continue to flow toward highly monitored and "visible" populations, whereas groups facing greater health risks but lower data visibility may be further excluded from preventive and promotional efforts.

Moreover, the digital divide poses a particularly salient challenge in AI-enabled health promotion. The expanding use of wearable devices, mobile health applications, and online platforms has rendered health monitoring increasingly dependent on digital infrastructures. Yet older adults, low-income populations, and individuals with limited technological access may be unable to participate fully in these systems. If such structural disparities are not explicitly addressed within public health governance, AI tools originally designed to advance health equity may instead function as technological mechanisms that reproduce and exacerbate existing inequalities.

4.3. Public health governance capacity and responsibility delineation

At the institutional level, the application of AI in public health promotion introduces significant challenges for existing governance capacities and mechanisms of responsibility delineation. First, in algorithm-supported decision-making processes, the identification of accountable actors becomes increasingly complex. When health risk identification or intervention recommendations rely in part on AI models, questions arise as to whether responsibility should rest with public authorities, technology providers, or the algorithmic systems themselves—an issue that remains insufficiently clarified[36]. In the absence of clearly defined responsibility boundaries, public health governance systems may encounter substantial difficulties in ensuring accountability when decision errors or adverse consequences occur.

Second, the capacity of public institutions to understand, evaluate, and regulate AI systems is a critical determinant of governance effectiveness. The technical complexity and opacity of many AI models render their decision-making logic difficult for administrators without specialized expertise to interpret. When public health authorities lack adequate technical literacy, governance power may shift implicitly toward technology companies or algorithm developers, thereby undermining the public sector's leadership role in health governance.

Finally, the boundary between commercial technology actors and public governance warrants sustained attention. While the development, maintenance, and updating of AI systems are often carried out by private enterprises, public health promotion is inherently oriented toward public values and collective interests. Without clear institutional arrangements and robust regulatory frameworks, commercial imperatives may come into tension with public health objectives and may compromise the fairness and transparency of decision-making processes. Accordingly, as AI-enabled health promotion continues to advance, ensuring the primacy of public interests and strengthening public sector governance capacity through institutional design emerges as an unavoidable and central governance task.

5. Discussion

5.1. Reframing the role of AI in public health

Debates on AI-enabled public health promotion must move beyond narrowly instrumental assessments of "whether the technology works" and toward a more systematic reflection on the role of AI within public health governance systems. The analysis in this study suggests that AI should be conceptualized primarily as a technological tool and infrastructural component embedded in public health systems, rather than as an autonomous decision-making actor. Its central contribution lies in enhancing the efficiency and quality of health monitoring, risk identification, and intervention feedback processes, rather than in substituting for the value judgments, policy trade-offs, and responsibility attribution that underpin public health decision-making[37].

From a governance standpoint, public health decision-making is fundamentally a process in which normative considerations and technical reasoning are tightly interwoven, encompassing both the use of scientific evidence and deliberations over equity, efficiency, and broader social values[38]. Although AI can provide substantial analytical support in data processing and pattern recognition, its outputs lack independent normative legitimacy. Accordingly, framing AI as a "decision support system" rather than a "decision-making agent" is a critical condition for preventing technical rationality from superseding public rationality[39]. Absent this distinction, public health governance risks drifting toward forms of technological determinism that may erode the democratic foundations and accountability of policy processes.

Furthermore, viewing AI through an infrastructural lens facilitates its incorporation into long-term strategies for public health capacity building. Much like epidemiological surveillance systems or health information infrastructures—which do not themselves dictate policy directions—the role of AI is contingent upon the institutional environments and governance objectives within which it is deployed[40]. This perspective offers a crucial theoretical foundation for the design of subsequent policies and institutional arrangements.

5.2. Implications for public health policy and practice

At both the policy and practice levels, a central implication of AI-enabled public health promotion concerns the critical role of institutional design. Technological capacity alone does not automatically translate into improved governance performance; rather, the realization of its public value depends on clearly articulated regulatory frameworks, well-defined lines of responsibility, and robust procedural safeguards[41]. Accordingly, when incorporating AI tools into public health policy, it is essential to concurrently strengthen data governance arrangements, enhance algorithmic transparency, and establish accountability mechanisms, thereby preventing technological applications from expanding in advance of their institutional embedding.

Second, the analysis underscores the importance of developing human–machine collaborative models of public health governance. The strengths of AI in health monitoring and risk identification should complement—rather than supplant—the professional judgment and decision-making authority of public health practitioners[42]. By institutionalizing a division of labor in which humans retain responsibility for value-based judgments while machines are tasked with information processing, public health systems can improve efficiency without sacrificing professional expertise or ethical sensitivity. Such collaborative arrangements may also mitigate the structural disadvantages faced by public institutions in technical capacity, reducing the risk of governance authority shifting unilaterally toward technological systems or commercial actors.

More fundamentally, public health policy must remain alert to the potential risks associated with technology-dominated governance. When AI-generated outputs are treated as “neutral facts” without critical reflection, public health decision-making may inadvertently reproduce and reinforce existing patterns of inequality[43]. Therefore, alongside the practical adoption of AI, it is imperative to maintain ongoing mechanisms for the critical examination of algorithmic assumptions, data provenance, and broader social consequences, ensuring that technological applications remain firmly oriented toward the overarching goals of health equity and the public interest.

5.3. Research limitations and future directions

Despite the rapid growth of research on the application of AI in public health in recent years, the current evidence base remains predominantly conceptual and exploratory, with relatively limited empirical assessment of its long-term governance effects and institutional implications. Much of the existing literature focuses on technical feasibility or potential benefits, while comparative analyses examining how AI functions across diverse public health institutional settings remain insufficient[44]. This imbalance constrains the translation of scholarly insights into actionable policy and practice.Future research should therefore advance along several key directions. First, greater emphasis should be placed on empirical studies grounded in real-world public health contexts. By employing mixed-methods approaches that integrate quantitative and qualitative evidence, future work can more systematically assess the governance outcomes of AI interventions in health monitoring and health promotion. Second, long-term evaluation is essential. The effects of AI systems are likely to emerge gradually over time, and their implications for health inequalities, resource allocation, and governance structures require rigorous longitudinal investigation[45]. Third, cross-regional and cross-institutional comparative research holds particular promise. Substantial variation across countries and regions in public health governance models, data regimes, and technological infrastructures creates natural laboratories for examining the applicability and boundary conditions of AI-enabled governance approaches[46].Advancing research along these lines will enable a more precise and robust understanding of the roles, effects, and governance conditions of AI in public health promotion, and will help move the field beyond conceptual exploration toward more systematic and institutionalized applications.

6. Conclusion

As public health governance shifts from disease treatment toward health promotion and risk prevention, integrating physical health monitoring with public health promotion has become a fundamental requirement for system transformation. This study argues that AI, through multi-source data integration, health risk identification, and intelligent feedback mechanisms, can bridge the structural disconnect between monitoring and promotion by transforming health data into action-oriented governance resources. Importantly, AI should be understood as an enabling tool and infrastructure serving public health objectives, rather than an automated substitute for public decision-making. The effectiveness of AI-enabled public health promotion ultimately depends on governance capacity and institutional design. Only under conditions of clear accountability, robust data governance, and human–machine collaborative decision-making can technological potential be translated into sustainable health benefits. In this sense, AI drives not merely a technical upgrade of health monitoring, but a broader reconfiguration of public health promotion models and governance logics.

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