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Bridging prediction and action: An integrative review of frameworks, strategies, and enablers for translating machine learning outputs into public health interventions

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Abstract

Machine learning applications now generate predictions across multiple domains of public health practice, yet the conversion of these outputs into sustained interventions continues to occur unevenly. This integrative review examined how predictive outputs become actionable within public health systems and identified the mechanisms, conditions, and tensions that shape this process. Following Whittemore and Knafl's methodology (2005), a search across four databases yielded 25 studies that were synthesized through thematic analysis and cross-literature integration. The review found that actionability depends on more than technical performance; it arises from the interplay between model characteristics and the organizational, cognitive, and contextual environments in which outputs are received. Structured implementation pathways and human-AI collaboration appeared as recurring translation mechanisms, while governance, workforce readiness, and feedback systems functioned as key enablers. Interconnected technical, organizational, and human barriers consistently constrained translation efforts. A Prediction-to-Action Framework was developed to integrate these elements and to surface ongoing tensions, particularly around human oversight, standardization, and governance scope. The findings indicate that effective translation requires coordinated attention to socio-technical conditions rather than technical performance in isolation.

Keywords: Machine Learning; Public Health; Prediction-to-Action; Socio-Technical Systems; Governance; Feedback

1. Introduction

Machine learning is now routinely used to generate predictions that could inform public health decisions, yet the movement from these predictions to coordinated intervention remains inconsistent across settings. While predictive models have advanced in technical sophistication, many organizations still struggle to integrate outputs into routine decision-making and action. Existing reviews have primarily examined model development, predictive performance, or individual implementation contexts, but limited attention has been given to synthesizing the cross-cutting mechanisms, organizational conditions, and governance structures that enable translation across public health settings. At the same time, the potential benefits of successful translation are substantial, particularly for decision quality, resource allocation, and population outcomes. This review therefore set out to examine how machine learning outputs are translated into public health interventions and to develop a conceptual framework that can guide both research and practice in this area.

Machine learning applications in public health have expanded rapidly, with predictive models now deployed to stratify risk, forecast disease trends, allocate resources, and support operational decisions (Dada et al., 2024; Chang et al., 2025). These tools are intended to enhance the timeliness and precision of public health responses. Nevertheless, the extent to which predictive outputs translate into actual intervention varies considerably across settings and use cases.

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Although machine learning models frequently demonstrate strong predictive performance in controlled or retrospective analyses, their integration into routine decision-making remains limited in many contexts. A substantial proportion of studies continue to prioritize model accuracy and technical validation, with comparatively less attention devoted to how outputs are interpreted, acted upon, or sustained within complex organizational environments (Chang et al., 2025; Dada et al., 2024; Adnan et al., 2025). This pattern suggests that predictive capability alone does not guarantee improved public health action.

The gap between prediction and intervention arises from multiple interacting factors. Outputs may lack sufficient interpretability, fail to align with existing workflows, or encounter organizational resistance stemming from concerns about trust, accountability, or resource implications. Governance structures and workforce capacity further shape whether and how predictive information is utilized (Olawade et al., 2026; Oleribe et al., 2026). These challenges are compounded by the fragmented nature of the literature, which spans implementation science, health informatics, public health practice, and data science, often without adequate integration across disciplinary perspectives.

This review was undertaken to synthesize current evidence on the processes through which machine learning outputs become actionable within public health contexts. It focuses on identifying the mechanisms that support translation, the organizational and socio-technical conditions that enable or constrain it, and the tensions that persist across different approaches and settings.

Translation in this review refers not only to implementation of interventions but also to the broader socio-technical pathway through which machine learning outputs are transformed from predictive information into actionable decisions, operational responses, and measurable public health activities. This encompasses workflow integration, organizational response mechanisms, clinical or operational decision support, and the implementation of resulting actions at individual, organizational, or population levels.

This integrative review seeks to:

- identify the mechanisms through which machine learning outputs are translated into public health action;
- examine organizational and socio-technical enablers that facilitate or hinder translation;
- synthesize persistent barriers that constrain the movement from prediction to intervention;
- develop an integrative conceptual framework to guide research and practice in prediction-to-action translation.

2. Methods

2.1. Review Design

This integrative review followed Whittemore and Knafl's methodology (2005). This approach was selected because it allows for the synthesis of diverse forms of evidence, including empirical studies, conceptual papers, and policy documents. Such methodological flexibility is necessary when examining complex socio-technical processes such as the translation of machine learning outputs into public health action, where relevant evidence is dispersed across multiple disciplines and study designs.

2.2. Search Strategy

A comprehensive search was conducted across four major databases: PubMed, Scopus, Web of Science, and IEEE Xplore. Search terms combined concepts related to machine learning or artificial intelligence with terms related to implementation, translation, public health, and decision-making. The search was limited to studies published between January 2021 and June 2026 to capture the most recent developments in the field. Reference lists of relevant articles were also screened to identify additional studies.

2.3. Eligibility Criteria

2.3.1. Inclusion Criteria

- Focused on machine learning or artificial intelligence applications in public health or healthcare settings.
- Addressed the translation, implementation, or use of predictive outputs in decision-making or intervention processes.
- Published in English between 2021 and 2026.
- Comprised empirical studies, conceptual papers, framework development studies, or policy analyses.

2.3.2. Exclusion Criteria

- Focused solely on the technical development or validation of machine learning models without addressing their application or translation into practice.
- Comprised conference abstracts, editorials, or commentaries without substantive analysis.
- Examined only clinical decision support in highly specialized medical settings without broader public health relevance.

2.4. Quality Appraisal

Given the integrative nature of this review and the inclusion of conceptual and policy-oriented literature alongside empirical studies, no single standardized quality appraisal tool (such as MMAT, JBI, or CASP) was applied to all studies. Instead, quality was considered through the lens of methodological transparency, relevance to the review objectives, and contribution to understanding translation processes. Empirical studies were assessed for clarity of methods and findings, while conceptual and policy papers were evaluated based on the coherence of their arguments and their utility in informing the synthesis.

2.5. Data Extraction

Data were extracted from each included study using a structured extraction form. Extracted information included: study design and type, country or setting, public health domain, machine learning application, description of translation processes or mechanisms, organizational and socio-technical enablers, barriers to translation, feedback or learning processes, and any proposed frameworks or models.

2.6. Data Synthesis

Data were synthesized using a thematic synthesis approach combined with cross-literature integration. Initial codes were generated from the extracted data and organized into descriptive themes. These themes were then compared across studies to identify patterns of convergence, divergence, and complementarity. Higher-order analytical themes were developed to explain how machine learning outputs are translated into public health action. The synthesis was iterative, with themes refined through constant comparison with the original studies.

3. Results

3.1. Characteristics of Included Studies

The 25 studies included in this review comprised a heterogeneous mix of empirical, conceptual, and policy-oriented publications. Study designs included systematic reviews, framework development studies, empirical evaluations, case studies, and policy analyses. The majority originated from high-income countries, particularly the United States, United Kingdom, and Australia, with limited representation from low- and middle-income settings. Public health domains represented across the corpus included disease surveillance, health service delivery, population risk stratification, and policy evaluation. Machine learning applications focused predominantly on predictive modeling using structured data from electronic health records, administrative claims, and geospatial sources. Publication years clustered between 2021 and 2026, reflecting the rapid growth of interest in artificial intelligence applications within public health. This temporal concentration suggests an emerging but still maturing evidence base. The corpus demonstrated strong representation of organizational and governance perspectives, while studies addressing long-term implementation outcomes and cross-disciplinary integration remained comparatively limited.

3.2. Actionability of ML Outputs

Actionability emerged as a contested and multidimensional concept across the corpus. While some studies conceptualized actionability primarily in terms of technical attributes such as predictive accuracy and model performance, others emphasized its dependence on organizational, cognitive, and contextual factors that determine whether outputs can be meaningfully used in decision-making (Dada et al., 2024; Adnan et al., 2025; Huguet et al., 2024). This divergence reveals that actionability is not an inherent property of machine learning outputs but is instead co-constructed through the interaction between model characteristics and the environments in which they are deployed.

Interpretability emerged as a central determinant of actionability. Outputs that could be readily understood by end users, particularly those without advanced technical training, were more likely to influence decisions. In contrast, complex or opaque models often required additional translation layers, such as visualization tools or expert intermediaries, which could delay or dilute their impact (Chang et al., 2025; Olawade et al., 2026).

Timeliness also emerged as a critical factor. Outputs that aligned with existing decision cycles, such as daily operational planning or weekly resource allocation meetings, demonstrated higher uptake than those requiring new workflows or extended interpretation periods (Dada et al., 2024). Contextual relevance further shaped actionability. Studies examining operational settings, such as supply chain management and clinical workflows, showed that actionability increased when outputs directly addressed immediate resource constraints or workflow bottlenecks (Ssemujju & Solomon, 2026; Ratcliffe et al., 2026). In contrast, studies focused on population-level surveillance emphasized proactive risk stratification and early intervention planning (Dada et al., 2024; Huguet et al., 2024).

Decision alignment and operational feasibility were frequently cited as practical constraints. Even when outputs were accurate and interpretable, they were often not acted upon if they conflicted with existing protocols, resource limitations, or professional judgment. Several studies noted tensions between model-driven recommendations and the need for human oversight, particularly in high-stakes public health decisions (Chang et al., 2025; Olawade et al., 2026). This tension was especially evident in contexts where algorithmic outputs challenged established practices or required significant organizational change.

At the population level, actionability appeared more challenging to achieve. While some studies demonstrated successful use of predictive outputs for targeted interventions (Dada et al., 2024; Fedcap Group, 2026), others highlighted difficulties in translating population-level risk scores into coordinated, equitable, and sustained public health responses (Ratcliffe et al., 2026; Wolff et al., 2021). Variability across contexts was pronounced, with studies consistently showing that the same modeling approach could yield highly actionable outputs in one setting and limited utility in another, depending on governance structures, data infrastructure, and workforce capacity (Dada et al., 2024; Ssemujju & Solomon, 2026; Chang et al., 2025).

3.3. Translation Mechanisms

Translation mechanisms describe the processes through which machine learning outputs move from prediction to intervention. Across the corpus, these mechanisms varied considerably in structure, scope, and degree of formalization. Some studies emphasized highly structured, phased implementation pathways (Nilsen et al., 2023; Huguet et al., 2024), while others highlighted more adaptive, context-responsive approaches (Adnan et al., 2025; Panteli et al., 2025). This variation reflects differing assumptions about how organizations convert predictive intelligence into coordinated action.

Structured implementation pathways, particularly those drawing on adapted quality improvement frameworks, provided detailed stage-based guidance for moving from model development to sustained use. These approaches typically included sequential phases of exploration, preparation, implementation, and sustainment, with explicit checkpoints for organizational readiness and governance review. Such pathways were associated with more systematic adoption, especially in settings with established implementation infrastructure (Nilsen et al., 2023; Oleribe et al., 2026). However, their rigidity sometimes limited responsiveness in rapidly evolving public health contexts or resource-constrained environments (Adnan et al., 2025).

Human-AI collaborative mechanisms emerged as an important but inconsistently applied approach. Combining algorithmic outputs with human judgment improved decision quality and reduced the risks associated with fully automated recommendations. Effective collaboration depended on clearly defined roles, escalation protocols, and sufficient time for review. In contrast, mechanisms that minimized human involvement often encountered resistance or produced unintended consequences when outputs conflicted with professional expertise or local knowledge (Olawade et al., 2026; Chang et al., 2025).

Decision support architectures and workflow integration mechanisms also shaped translation effectiveness. Outputs that were embedded within existing clinical or operational workflows demonstrated higher rates of use than those requiring new processes or external interpretation (Dada et al., 2024). Workflow integration was facilitated by decision support tools that presented actionable options rather than raw predictions. However, poor integration frequently resulted in outputs being ignored or overridden, even when technically sound (Chang et al., 2025).

Organizational translation processes and governance-mediated mechanisms played a central role in scaling and sustaining translation efforts. Studies highlighted the importance of leadership engagement, cross-departmental coordination, and formal accountability structures (Oleribe et al., 2026; Freeman et al., 2025). Governance mechanisms that clarified decision rights and escalation pathways supported more consistent action, particularly when predictive outputs had implications across multiple organizational units (Sedeeq et al., 2025). In contrast, weak governance often led to fragmented responses or inaction despite clear predictive signals (Adnan et al., 2025).

Escalation and response pathways were critical in high-stakes or time-sensitive situations. Effective mechanisms included predefined thresholds for action, designated response teams, and feedback channels that allowed frontline users to report implementation challenges (Olawade et al., 2026). These elements helped bridge the gap between prediction and intervention but were inconsistently present across the corpus.

3.4. Organizational and Socio-Technical Enablers

Organizational and socio-technical enablers represent the conditions that facilitate the movement of machine learning outputs into sustained public health action. Across the corpus, governance structures emerged as one of the most consistently identified enablers. Effective governance provided clarity regarding decision-making authority, accountability mechanisms, and ethical oversight (Oleribe et al., 2026). Studies emphasized that both organizational-level governance frameworks and broader legal or policy structures influenced the feasibility of responsible AI adoption (Sedeeq et al., 2025; Freeman et al., 2025). Where governance was fragmented or underdeveloped, translation efforts frequently stalled despite technically sound predictive models (Adnan et al., 2025).

Leadership support was closely linked to governance effectiveness. Organizations with visible executive sponsorship and dedicated leadership for AI initiatives demonstrated greater capacity to mobilize resources and navigate implementation challenges (Freeman et al., 2025; Oleribe et al., 2026). Leadership engagement also helped legitimize new workflows and encouraged cross-departmental collaboration.

Workforce readiness and organizational readiness were identified as interdependent enablers. Workforce AI literacy, including the ability to interpret outputs, understand limitations, and integrate predictions into professional judgment, was repeatedly highlighted as a foundational requirement (Acosta, 2025). Several studies noted that low baseline AI literacy among public health and healthcare professionals constrained the effective use of even well-designed decision support tools (Kumar et al., 2025; Abdelwanis et al., 2026). Organizational readiness extended beyond individual competencies to include cultural openness to data-driven approaches, established change management processes, and alignment between AI initiatives and existing strategic priorities (Adnan et al., 2025).

Technical infrastructure and data ecosystems formed another critical layer of enabling conditions. Reliable data quality, interoperability across systems, and adequate computing resources were prerequisites for generating timely and relevant outputs. Organizations with mature data infrastructures were better positioned to move from model development to operational use. However, many public health settings continued to face significant limitations in data accessibility and system integration, which restricted the practical utility of predictive analytics (Chang et al., 2025; Adnan et al., 2025; Ahmed et al., 2023).

Implementation capacity and trust-building mechanisms further shaped translation outcomes. Organizations with dedicated implementation teams, change management expertise, and structured training programs were more successful in embedding machine learning outputs into routine practice (Nilsen et al., 2023; Freeman et al., 2025). Trust emerged as a relational enabler that developed through transparency about model performance, clear communication of uncertainty, and demonstrated alignment between algorithmic recommendations and professional values. Where trust was low, even actionable outputs were often disregarded (Olawade et al., 2026; Chang et al., 2025).

3.5. Persistent Translation Barriers

Barriers to translating machine learning outputs into public health action were frequently described as interconnected and mutually reinforcing rather than isolated obstacles. Technical barriers, including limited model generalizability, poor performance on underrepresented populations, and difficulties integrating outputs into existing systems, constrained the initial utility of predictive models. These technical limitations were often compounded by data quality barriers, such as incomplete records, inconsistent coding practices, and fragmented data sources across organizations. Poor data quality reduced both the reliability of predictions and the confidence with which decision-makers could act on them (Chang et al., 2025; Ahmed et al., 2023).

Organizational barriers played a central role in limiting translation. Many studies identified rigid hierarchies, siloed departments, and competing priorities as factors that slowed or blocked the adoption of data-driven approaches (Hassan et al., 2024; Adnan et al., 2025). In some cases, organizational cultures that prioritized established routines over innovation created resistance to new workflows generated by predictive outputs. These organizational challenges frequently interacted with workforce barriers, particularly low levels of AI literacy and limited capacity to interpret or act on model outputs. Frontline staff often lacked the training or time needed to meaningfully engage with predictive information, resulting in outputs being overlooked or overridden (Abdelwanis et al., 2026; Kumar et al., 2025).

Trust and adoption barriers further impeded translation. Several studies noted that skepticism toward algorithmic recommendations, concerns about loss of professional autonomy, and previous negative experiences with poorly implemented technologies reduced willingness to act on machine learning outputs (Abdelwanis et al., 2026; Chang et al., 2025). These trust-related barriers were especially pronounced when outputs conflicted with clinical or operational judgment or when the reasoning behind predictions was not transparent.

Ethical and regulatory barriers added additional layers of complexity. Questions regarding data privacy, algorithmic bias, accountability for automated decisions, and compliance with evolving regulations created hesitation among organizations considering broader deployment of predictive tools. In some contexts, unclear regulatory guidance slowed implementation even when technical and organizational conditions were favorable (Sedeeq et al., 2025; Adnan et al., 2025).

Resource constraints, including limited funding, insufficient technical expertise, and competing demands on staff time, consistently appeared as cross-cutting barriers (Hassan et al., 2024). These constraints disproportionately affected smaller or less-resourced public health organizations, widening disparities in the ability to translate predictive capabilities into action (Hassan et al., 2024).

3.6. Feedback and Learning Processes

Feedback and learning processes were identified as essential but inconsistently developed components of translating machine learning outputs into sustained public health action. Monitoring systems formed the foundation of these processes (Krelle et al., 2026). The importance of ongoing performance monitoring after deployment, including tracking predictive accuracy, identifying bias, and assessing real-world impact, was noted. However, systematic post-implementation monitoring was often limited by resource constraints and the absence of dedicated evaluation infrastructure (Chang et al., 2025).

Model updating processes and drift detection mechanisms were described as critical for maintaining the relevance of predictive outputs over time. Studies noted that models trained on historical data could degrade in performance due to changes in population characteristics, clinical practices, or external conditions (Li et al., 2025; Krelle et al., 2026). Effective drift detection required not only technical surveillance of model outputs, but also organizational capacity to interpret signals and initiate timely updates.

Feedback loops connecting implementation experiences back to model refinement and organizational decision-making were highlighted as important for continuous improvement. Structured mechanisms enabling frontline users to report implementation challenges or unexpected outcomes were described as facilitating iterative adjustments. Organizational learning processes that captured lessons from both successful and failed translation efforts were similarly noted, particularly in organizations with strong cultures of data-driven improvement and dedicated evaluation capacity (Kamel et al., 2024; Krelle et al., 2026).

Adaptive governance emerged as a higher-order mechanism supporting feedback and learning. Organizations that maintained flexible governance structures were better able to respond to new evidence generated through monitoring and evaluation. This included revising implementation protocols, reallocating resources, and updating decision rules in light of ongoing performance data. In contrast, rigid governance arrangements often delayed or prevented necessary adaptations, even when monitoring systems identified clear problems (Centers for Disease Control and Prevention, 2026).

3.7. Cross-Literature Integration

The corpus revealed both notable convergences and persistent divergences across disciplinary perspectives on translating machine learning outputs into public health action. Studies rooted in implementation science and health services research converged around the importance of structured processes, organizational readiness, and governance as foundational to successful translation (Nilsen et al., 2023; Oleribe et al., 2026). These fields consistently emphasized phased implementation approaches, stakeholder engagement, and the need to address multi-level barriers. In contrast, contributions from health informatics and data science more frequently focused on technical considerations such as model performance, data quality, and system integration (Chang et al., 2025). While these perspectives were not inherently contradictory, they often operated in parallel rather than in direct dialogue, resulting in limited integration of technical and socio-organizational insights within individual studies (Gao et al., 2026).

Interdisciplinary differences were also evident in how actionability and implementation success were conceptualized. Public health and policy-oriented studies tended to frame success in terms of population-level impact, equity, and system-wide coordination (Fedcap Group, 2026). Implementation science literature placed greater weight on fidelity to planned processes and sustainability of adoption (Nilsen et al., 2023; Huguet et al., 2024). Machine learning and informatics studies more commonly evaluated success through metrics of predictive accuracy and operational efficiency (Li et al., 2025). These differing priorities contributed to divergent recommendations regarding where investment and attention should be directed.

Contradictory findings appeared most clearly in discussions of automation versus human oversight. Some studies advocated for greater automation to improve speed and consistency of decision-making, while others stressed the necessity of sustained human involvement to ensure safety, contextual judgment, and accountability (Olawade et al., 2026; Chang et al., 2025). Complementary findings were more common regarding the role of governance and workforce capacity, where studies from multiple disciplines converged on the need for both structural oversight and human skill development, albeit with different emphases on how these should be achieved (Oleribe et al., 2026; Nilsen et al., 2023).

Cross-literature tensions were most visible in the treatment of feedback and adaptation. While implementation science literature increasingly highlighted the importance of continuous learning and iterative refinement (Krelle et al., 2026), many machine learning studies focused primarily on initial model development and validation, with less attention to post-deployment monitoring and adjustment (Li et al., 2025; Chang et al., 2025). This divergence points to a broader gap in how different fields conceptualize the full lifecycle of machine learning applications in public health settings.

Emerging meta-patterns suggest that effective translation requires bridging technical optimization with socio-technical integration. Studies that combined insights from multiple disciplines were more likely to address both the design of predictive tools and the organizational conditions necessary for their use (Gao et al., 2026; Fontaine et al., 2026). However, such integrative work remained relatively limited within the corpus. The evidence indicates that while individual disciplinary perspectives offer valuable contributions, greater synthesis across fields is needed to develop comprehensive approaches to translating machine learning outputs into coordinated and sustained public health action.

3.8. Proposed Prediction-to-Action Framework

The proposed Prediction-to-Action Framework was developed to synthesize the key findings from the 25-study corpus and to provide a structured yet dynamic representation of how machine learning outputs can be translated into public health interventions. As illustrated in Figure 1, the framework positions translation not as a linear sequence but as an interconnected, socio-technical process involving multiple interacting components.

The framework begins with **Contextual Inputs**, which include predictive models, available data infrastructure, population characteristics, and the specific decision needs of public health organizations. These inputs do not automatically lead to action. Instead, they must pass through **Decision Nodes**, where outputs are interpreted in light of professional judgment, organizational priorities, available resources, and time constraints. The quality and nature of interpretation at these nodes significantly influence whether predictions result in meaningful intervention.

Translation Mechanisms form the central processes through which predictive outputs move toward action. These include structured implementation pathways, human-AI collaborative decision-making, strategic integration approaches, and workflow-embedded decision support. The framework recognizes that multiple mechanisms often operate simultaneously and that their effectiveness is highly dependent on alignment with local organizational context.

Surrounding these mechanisms are **Enabling Conditions**, which support or constrain translation. These encompass multi-level governance structures, leadership engagement, workforce AI literacy, technical infrastructure, and organizational readiness. The framework treats these enablers as interdependent rather than isolated factors.

Barrier Structures operate in parallel with enabling conditions. Technical limitations, data quality issues, organizational resistance, workforce skill gaps, ethical and regulatory constraints, and resource limitations can disrupt translation at multiple points in the process.

Feedback Processes provide the adaptive capacity of the framework. These include post-implementation monitoring, drift detection, model updating, and organizational learning mechanisms. Feedback loops connect implementation experiences back to earlier components, allowing for refinement of models, adjustment of translation mechanisms, and strengthening of enabling conditions over time.

The framework explicitly includes **Tension Nodes** to acknowledge areas of persistent friction identified across the corpus. These include tensions between human oversight and automation, between standardization and contextual adaptation, and between technical optimization and socio-technical integration. These tensions are not presented as problems to be eliminated but as dynamics that must be actively managed.

Finally, the framework points toward **Expected Outcomes**, which include improved decision quality, timelier and coordinated public health responses, enhanced resource allocation, and, ultimately, better population health impact. These outcomes are not guaranteed but depend on the effective functioning and interaction of all preceding components.

The relationships among components in Figure 1 are dynamic and bidirectional. Enabling conditions influence the selection and effectiveness of translation mechanisms, while feedback processes can strengthen or weaken both enablers and mechanisms over time. This interconnected structure underscores one of the central findings of the review: isolated improvements in any single component (such as model accuracy or governance alone) are unlikely to produce sustained translation success. The framework therefore provides both a diagnostic tool for understanding current translation challenges and a guide for designing more comprehensive implementation strategies.

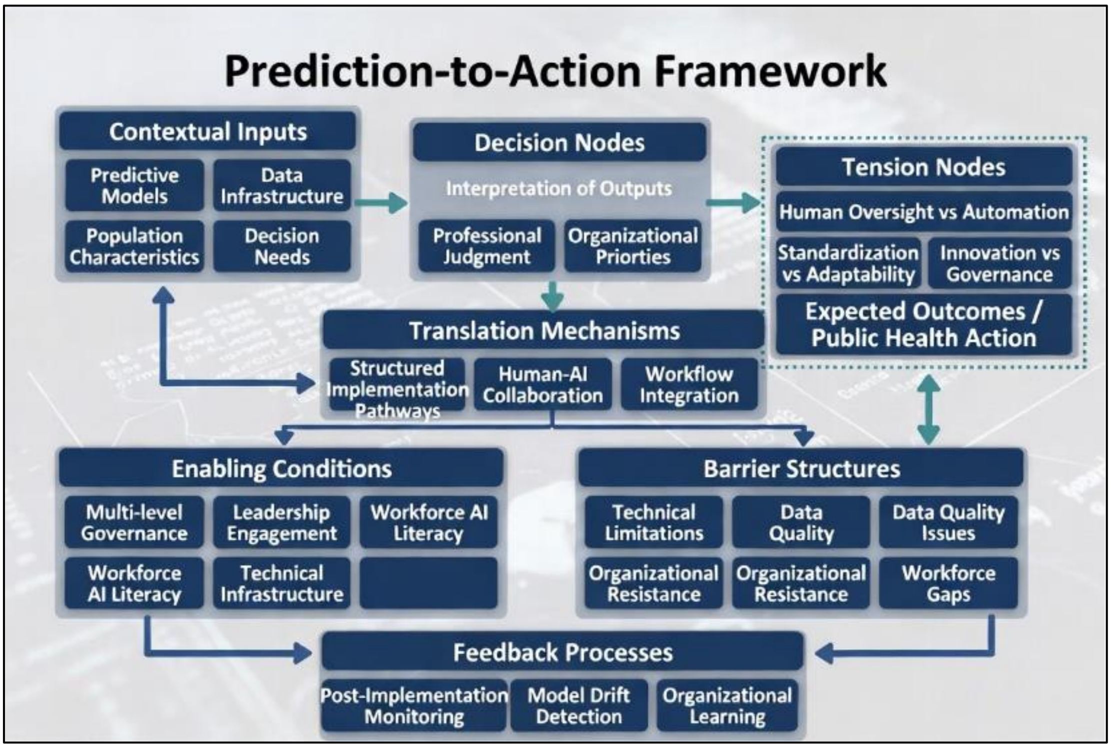

Figure 1 Proposed Prediction-to-Action Framework for Translating Machine Learning Outputs into Public Health Interventions (Author's construct, 2026).

4. Discussion

4.1. Principal Findings

This integrative review demonstrates that translating machine learning outputs into public health interventions is fundamentally a socio-technical process rather than a purely technical one. The findings reveal that actionability is not an inherent property of predictive models but emerges from the interaction between model characteristics and the organizational, cognitive, and contextual environments in which they are received. Multiple translation mechanisms operate in parallel, including structured implementation pathways, human-AI collaborative decision-making, workflow integration, and governance-mediated processes. Organizational governance, leadership support, workforce AI literacy, technical infrastructure, and trust consistently emerged as critical enablers, while technical limitations, organizational resistance, workforce skill gaps, and resource constraints acted as persistent and interconnected barriers. Feedback and learning processes were identified as essential for sustained translation but remain underdeveloped in current practice. The review also highlights significant disciplinary fragmentation in the literature, underscoring the need for greater cross-disciplinary synthesis.

4.2. Comparison with Previous Reviews

Previous reviews in implementation science have emphasized phased approaches to adoption and the importance of organizational readiness and stakeholder engagement. Reviews in health informatics have largely concentrated on technical performance, data quality, system integration, and user acceptance of decision support tools. Public health AI reviews have tended to focus on specific applications such as disease surveillance or risk prediction, often highlighting predictive accuracy and implementation barriers within particular disease domains. While these bodies of work provide valuable insights, they have generally remained within disciplinary boundaries and have not systematically examined the full pathway from prediction to coordinated public health action. This review differs by adopting an integrative approach that spans implementation science, health informatics, and public health, with explicit attention to the mechanisms, enablers, barriers, and feedback processes that connect predictive outputs to intervention. It also contributes a novel conceptual framework that makes visible the dynamic relationships and persistent tensions involved in this translation process.

4.3. Implications for Practice

Public health agencies and health departments should prioritize investment in governance structures and workforce AI literacy alongside technical implementation. Clear decision rights, escalation pathways, and accountability mechanisms are necessary to support consistent use of predictive outputs. AI developers should design tools with interpretability, timeliness, and workflow integration in mind, rather than focusing solely on predictive performance. Decision makers at organizational and system levels need to recognize that successful translation requires attention to socio-technical conditions, including trust-building, change management, and ongoing feedback systems. Implementation efforts should be tailored to local context rather than assuming that technically robust models will automatically lead to action.

4.4. Policy Implications

Policy efforts should support the development of adaptive governance frameworks that balance accountability with flexibility. Clear standards for the responsible use of predictive analytics in public health are needed, particularly regarding data quality, model transparency, equity considerations, and post-implementation monitoring. Regulatory approaches should encourage organizations to invest in evaluation infrastructure and feedback systems rather than focusing exclusively on initial model deployment. Policies that promote cross-disciplinary collaboration and knowledge sharing between implementation science, health informatics, and public health practice would help address the current fragmentation in the field.

4.5. Implications for Future Research

Significant gaps remain in understanding the long-term outcomes of machine learning implementation in public health settings. Future research should examine prevention-oriented translation pathways and the effectiveness of different mechanisms in low-resource contexts. Greater attention is needed to strategies for integrating insights across technical, organizational, and governance domains. Studies that employ longitudinal designs and mixed methods would strengthen understanding of how translation processes evolve. Research addressing conceptual heterogeneity and developing shared terminology across disciplines would also support more cumulative knowledge building in this emerging area.

4.6. Strengths of the Review

This review provides a comprehensive synthesis of diverse study types using an integrative methodology that permits the inclusion of empirical, conceptual, and policy-oriented literature. It explicitly addresses conceptual tensions and preserves contradictory findings rather than forcing artificial consensus. The development of the Prediction-to-Action Framework offers a structured yet adaptable tool for both research and practice. The cross-literature integration approach helps bridge disciplinary silos that have characterized previous work in this area.

Limitations

This review has several limitations. The search was restricted to English-language publications, which may have excluded relevant studies from non-English-speaking contexts. Publication bias may have influenced the availability of studies reporting negative or null findings regarding translation efforts. The included studies were heterogeneous in design, setting, and focus, which limited the ability to conduct quantitative synthesis. Representation from low- and middle-income countries was limited, constraining the generalizability of findings to resource-constrained settings. Conceptual heterogeneity across studies, particularly in the use of terms such as actionability, implementation, and translation, required interpretive judgment during synthesis.

5. Conclusion

Translating machine learning outputs into public health interventions is fundamentally a socio-technical process. While predictive models can generate valuable insights, their impact depends on the alignment of organizational governance, workforce capacity, structured translation mechanisms, and ongoing feedback systems. The review reveals that technical performance alone is insufficient; enabling conditions and adaptive learning processes are equally critical to achieving sustained action.

The proposed Prediction-to-Action Framework offers a structured approach for understanding these interdependencies. By explicitly incorporating enabling conditions, barrier structures, feedback processes, and persistent tensions, the framework provides a practical guide for both research and implementation. It advances existing models by integrating machine learning considerations with implementation science principles while remaining grounded in the realities of public health systems.

For public health, these findings underscore the need to move beyond isolated technical investments toward coordinated strategies that strengthen governance, build workforce readiness, and embed continuous learning into routine practice. Addressing the identified tensions, particularly those concerning human oversight, standardization, and governance, will be essential for realizing the potential of machine learning to improve population health outcomes.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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