Advancing U.S. Public Health Surveillance: Leveraging Generative AI and Agentic Systems for the National HIV Behavioral Surveillance Program

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***Abstract*—This comprehensive technical paper responds to the Centers for Disease Control and Prevention's Federal Register notice (Docket No. CDC-2025-0753) concerning the revision of the National HIV Behavioral Surveillance System (NHBS). We propose an integrated framework leveraging Generative AI (GenAI) and agentic systems to enhance the NHBS data collection methodology across 21 Metropolitan Statistical Areas (MSAs). Our approach addresses all five evaluation criteria specified by the Office of Management and Budget: (1) necessity and practical utility, (2) accuracy of burden estimates, (3) enhancement of data quality, utility, and clarity, (4) minimization of respondent burden through technology, and (5) assessment of information collection costs. Drawing on recent research in AI-assisted surveying, we demonstrate how Large Language Models (LLMs), adaptive interviewing systems, and human-AI hybrid frameworks can transform NHBS from a periodic cross-sectional survey into a dynamic, real-time surveillance tool while reducing the estimated 3,398-hour annual burden. We provide detailed implementation recommendations for the proposed three-year cycle, addressing ethical considerations, validation requirements, and quality assurance protocols for deployment in public health settings. This expanded framework includes comprehensive technical specifications, cost-benefit analyses, and risk mitigation strategies to support evidence-based decision-making for CDC leadership.**

***Index Terms*—Public Health Surveillance, HIV Prevention, Generative AI, Large Language Models, Adaptive Interviewing, Data Collection Methodology, Human-AI Collaboration, Digital Health Innovation, Cross-Validation, Ethical AI.**

I. Introduction

The National HIV Behavioral Surveillance System (NHBS) represents a critical component of the United States' public health infrastructure, systematically collecting behavioral data from populations at highest risk for HIV infection: Men who have Sex with Men (MSM), Persons Who Inject Drugs (PWID), and Heterosexually Active Persons at Increased Risk (HET). As the Centers for Disease Control and Prevention (CDC) seeks approval for a three-year revision of NHBS data collection across 21 Metropolitan Statistical Areas (MSAs), this period presents a strategic opportunity to modernize surveillance methodology through artificial intelligence (AI) integration.

Traditional survey methods, while valuable, face significant challenges including respondent burden, data latency, scalability limitations, and inconsistent quality across multiple sites. The current NHBS methodology estimates 3,398 annual burden hours across screening interviews, behavioral assessments, and recruiter debriefings [**?**]. Recent advancements in AI, particularly Generative AI (GenAI) and agentic systems, offer transformative potential to address these limitations while enhancing data quality and public health utility.

A. The Evolution of Survey Methodology

Survey-based public health surveillance has undergone significant evolution over the past decades, moving from paper-based questionnaires to computer-assisted interviewing systems. However, these advances have primarily focused on data capture efficiency rather than fundamental improvements in respondent experience or data quality. Recent developments in conversational AI and natural language processing present an opportunity to reimagine the survey experience entirely [1].

B. Current Challenges in NHBS Implementation

The NHBS faces several persistent challenges that limit its effectiveness:

- **Respondent Burden:** Extended interview times (averaging 45-60 minutes) create barriers to participation, particularly among populations with complex life circumstances.
- **Sampling Biases:** Respondent-driven sampling (RDS) chains can become trapped in social network clusters, limiting demographic diversity [2].
- **Data Quality Variability:** Inconsistent interviewer training and administration across 21 MSAs introduces systematic biases and quality variations.
- **Language and Cultural Barriers:** Limited multilingual capacity and cultural adaptation restrict participation from diverse communities [3], [4].
- **Delayed Actionability:** Lengthy data processing cycles prevent timely public health response to emerging trends.

C. The AI Transformation Opportunity

This paper provides a comprehensive technical framework for integrating AI technologies into NHBS, drawing on evi-

Cite as: Satyadhar Joshi , Jan 2026, *Advancing U.S. Public Health Surveillance: Leveraging Generative AI and Agentic Systems for the National HIV Behavioral Surveillance Program*, Comment submitted to Centers for Disease Control and Prevention (CDC) Regulations.gov
https://downloads.regulations.gov/CDC-2025-0753-0005/attachment_1.pdf

dence from recent research in healthcare AI, survey methodology, and human-AI collaboration. We structure our recommendations according to the five evaluation criteria specified by the Office of Management and Budget (OMB), providing specific implementation pathways for each component of the NHBS data collection process.

II. Technical Specifications and Methodological Implementation

This section provides detailed technical specifications, architectural diagrams, and implementation considerations for the proposed AI-enhanced NHBS framework, drawing extensively on recent research in LLM-based multi-agent systems [5], [6] and agentic AI architectures [7].

A. Architectural Overview

The proposed AI-enhanced NHBS system follows a multi-agent architecture with modular components designed for scalability, privacy, and adaptability across diverse public health settings. Recent advances in LLM-based multi-agent systems demonstrate that "LLM-based Multi-Agent Systems (LLM-MAS) have become a research hotspot since the rise of large language models" with applications in solving complex tasks and simulating specific scenarios [5].

1) System Architecture: Figure 1 illustrates the comprehensive system architecture integrating traditional NHBS components with AI-enhanced capabilities:

The architecture implements a hybrid human-AI approach where "generative AI offers transformative opportunity to address challenges by augmenting human expertise with advanced computational capabilities" [8]. Each agent operates independently but coordinates through shared protocols and human oversight mechanisms.

B. Agent Specifications and Prompt Engineering

Effective implementation requires careful prompt engineering and agent configuration. Research shows that "prompt engineering has emerged as an indispensable technique for extending capabilities of large language models" [10]. Figure 2 details the workflow for the primary interview agent:

The prompt engineering follows systematic approaches documented in comprehensive surveys [11], [12], including:

- **Chain-of-Thought Prompting**: For complex reasoning about risk behaviors
- **Few-shot Learning**: Providing examples of culturally appropriate phrasing
- **Role-based Prompts**: Defining agent personas (e.g., "public health interviewer")
- **Constraint Prompts**: Ensuring ethical boundaries and privacy compliance

C. Data Flow and Privacy Architecture

Figure 3 illustrates the privacy-preserving data flow architecture implementing federated learning principles [13]:

This architecture ensures that "conversational AI platforms can transform healthcare delivery while addressing implementation challenges including accuracy, privacy, bias, and regulatory compliance" [9].

D. Validation and Monitoring Framework

Comprehensive validation follows established cross-validation protocols [15], [16] with continuous monitoring. Figure 4 shows the multi-layered validation approach:

E. Implementation Timeline and Resource Requirements

Table I outlines the phased implementation approach:

F. Technical Infrastructure Requirements

The system requires specific technical infrastructure:

- **Compute Resources**: Cloud-based GPU instances for model inference and training
- **Storage**: Secure, HIPAA-compliant data storage with encryption at rest and in transit
- **Networking**: Low-latency connections for real-time interview processing
- **Security**: Multi-factor authentication, audit logging, and intrusion detection
- **APIs**: RESTful APIs for integration with existing NHBS systems and EHRs

G. Integration with Existing Systems

Successful implementation requires seamless integration with existing NHBS infrastructure:

- **NHBS Database**: API-based integration for data exchange
- **EHR Systems**: HL7/FHIR interfaces for clinical data (with consent)
- **Public Health Reporting**: Automated reporting to CDC surveillance systems
- **Community Services**: Referral systems for prevention and treatment services

H. Quality Assurance Protocols

Continuous quality assurance follows established protocols for AI in healthcare [18], [23]:

1) **Daily**: Automated validation of all AI-generated content
2) **Weekly**: Human review of 10% of interviews for quality control
3) **Monthly**: Bias assessment and model performance evaluation
4) **Quarterly**: Community advisory board review and feedback incorporation
5) **Annually**: Comprehensive system audit and re-validation

This technical framework provides the foundation for implementing AI-enhanced NHBS while ensuring scientific rigor, ethical compliance, and practical utility across all 21 Metropolitan Statistical Areas.

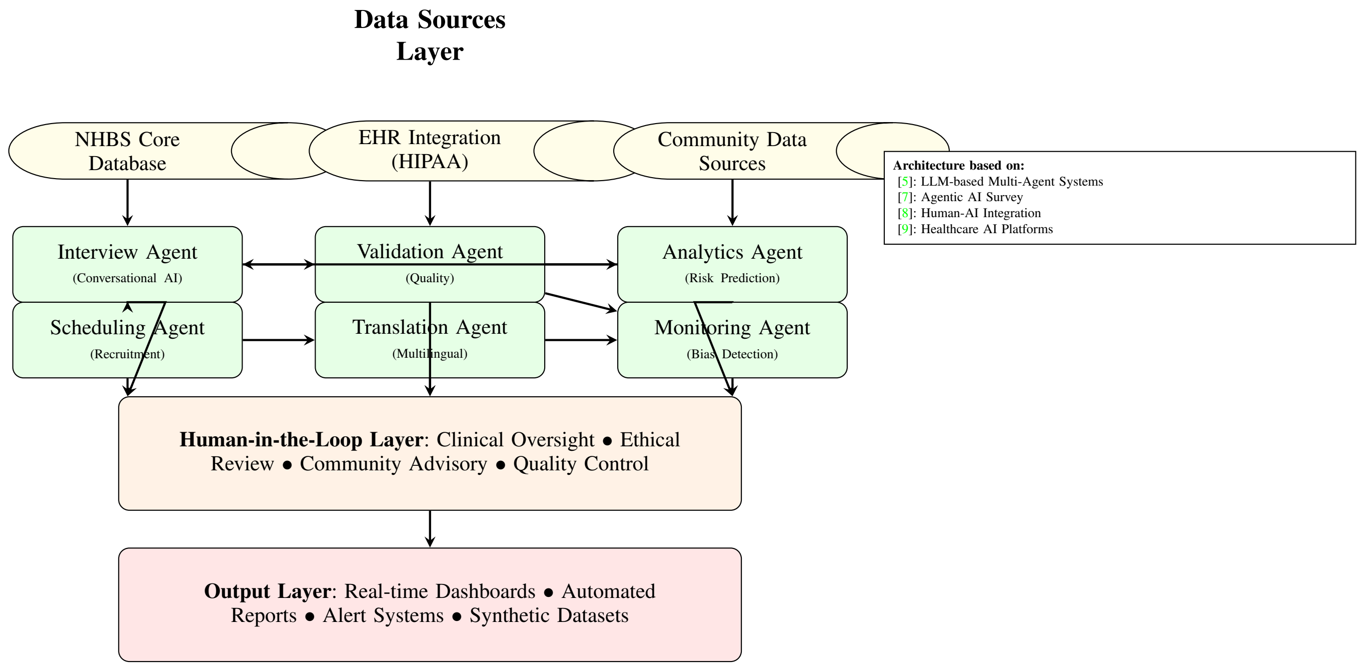

Fig. 1: Multi-Agent System Architecture for AI-enhanced NHBS Framework. This compact layout implements a federated multi-agent approach following LLM-MAS principles [5], [6], with human oversight ensuring ethical deployment [8] across all 21 MSAs.

TABLE I: Three-Year Implementation Timeline and Resource Requirements

Phase	Technical Components	Validation Requirements	Resource Allocation
Year 1: Pilot (MSM)	• Interview Agent • Basic Validation • Single MSA Deployment	• Technical Validation • User Acceptance Testing • Ethical Review	• 2 AI Developers • 1 Public Health Expert • Community Advisory Board
Year 2: Expansion (PWID)	• Multi-agent System • Translation Agent • 5 MSA Deployment	• Cross-cultural Validation • Clinical Validation • Bias Assessment	• 3 AI Developers • 2 Clinical Experts • Multilingual Support
Year 3: Full Scale (HET)	• Full Deployment • Predictive Analytics • All 21 MSAs	• Epidemiological Concordance • Public Health Impact • Cost-effectiveness Analysis	• Central Support Team • Local Implementation Teams • Continuous Monitoring

III. Necessity and Practical Utility Enhancement

The necessity of NHBS as a surveillance system is well-established, but its practical utility can be substantially enhanced through AI integration. Current methodologies provide valuable but delayed insights, with data processing and analysis occurring after field collection. GenAI systems can transform NHBS into a real-time surveillance tool with immediate public health applications.

A. *Real-time Data Synthesis and Analysis*

Recent research demonstrates that "integrating large language models (LLMs) into survey interviews shows early promise for improving response quality" [1]. The application of LLM-based conversational agents in healthcare settings has shown remarkable success, with studies reporting that participants "reported that the agent effectively conveyed the purpose of the survey, demonstrated good comprehension, and maintained an engaging interaction" [24].

For NHBS implementation, these capabilities enable several transformative applications:

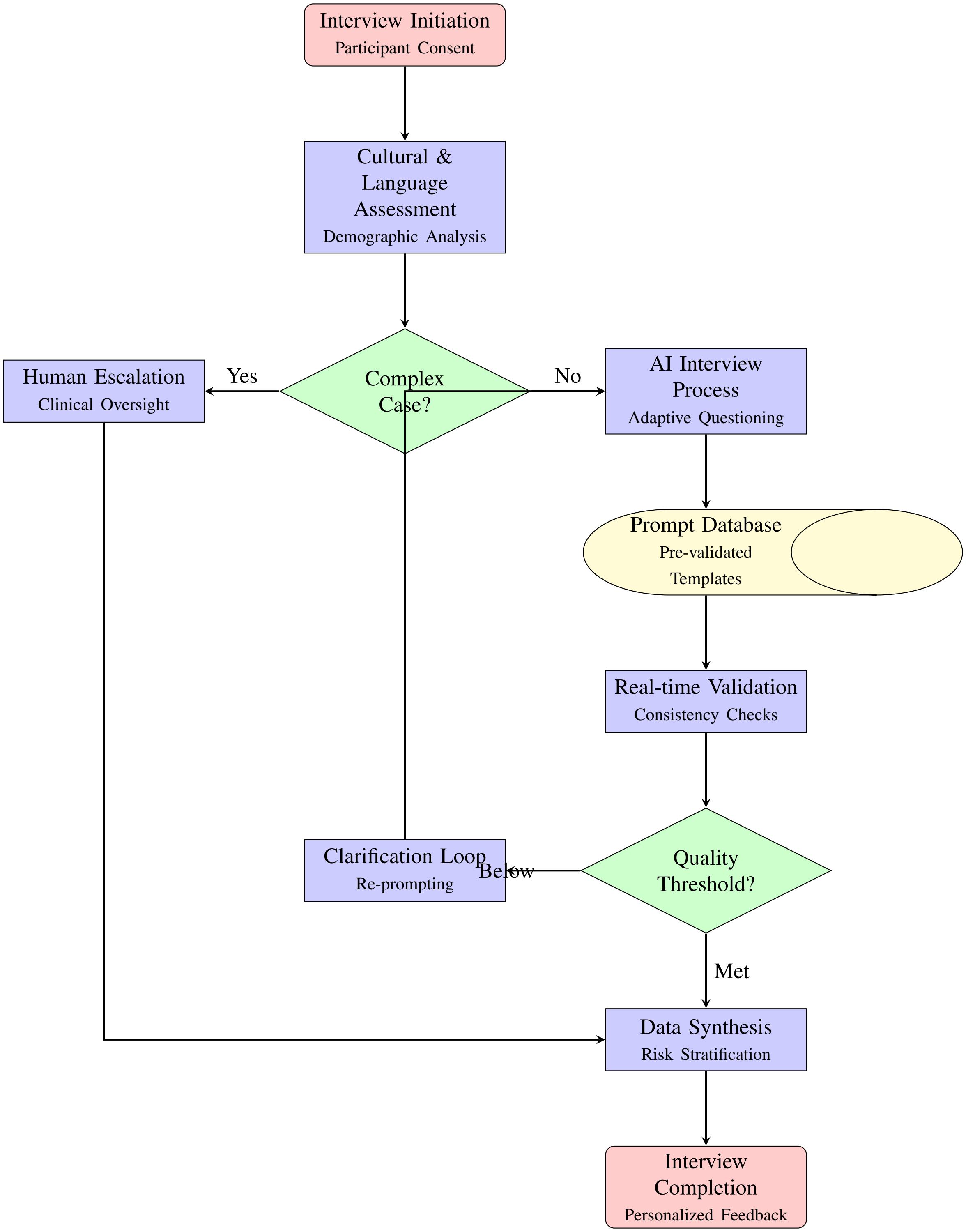

Fig. 2: Interview Agent Workflow with Human-in-the-Loop Escalation

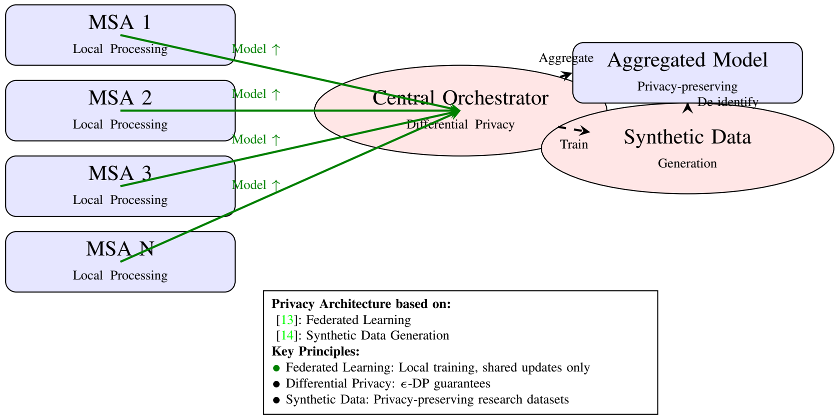

Fig. 3: Federated Learning Architecture for Privacy-preserving AI Training. This distributed architecture implements federated learning principles [13] where each MSA maintains local models, sharing only encrypted parameter updates. Differential privacy ensures mathematical protection against re-identification, while synthetic data generation [14] enables research without compromising participant confidentiality.

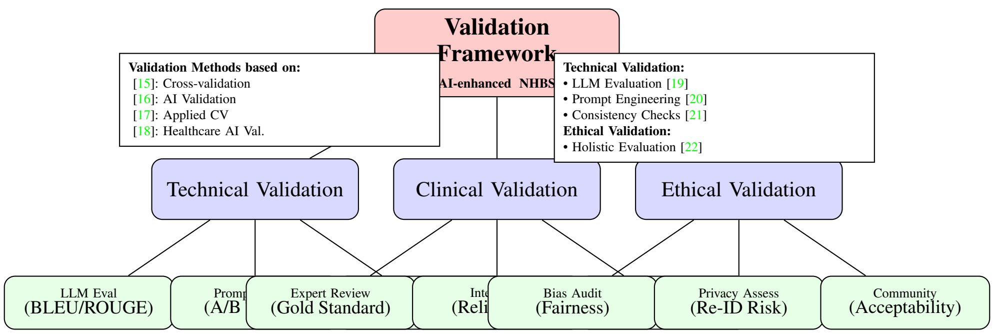

Fig. 4: Multi-layered Validation Framework for AI-enhanced NHBS following established cross-validation protocols [15], [16]. The framework implements comprehensive validation across technical [19], clinical, and ethical [22] dimensions, ensuring robust evaluation of AI systems in public health surveillance.

- **Immediate Risk Stratification:** AI systems can analyze responses in real-time to identify individuals at highest immediate risk, enabling prompt referral to prevention services such as PrEP initiation, HIV testing, or harm reduction programs. Unlike traditional post-hoc analysis, AI-driven risk assessment can provide actionable insights within seconds of interview completion.
- **Trend Detection:** Continuous analysis across interviews can detect emerging behavioral patterns before they manifest in epidemiological data. Machine learning algorithms can identify subtle shifts in risk behaviors, drug use patterns, or prevention service uptake that might signal emerging public health concerns.
- **Personalized Feedback:** During interviews, AI can generate tailored prevention recommendations based on individual risk profiles, increasing the intervention value of participation. This transforms NHBS from a purely observational tool to an active intervention platform, potentially improving participant motivation and retention.
- **Dynamic Questionnaire Adaptation:** AI systems can modify question sequences in real-time based on response patterns, ensuring comprehensive assessment while minimizing redundancy and respondent fatigue [25].

B. Dynamic Public Health Response

The integration of agentic AI systems allows NHBS to move beyond surveillance to active intervention support. Research on multi-agent systems in healthcare demonstrates their potential for "adaptive, efficient, and ethical healthcare" delivery [13]. In the NHBS context, this could involve:

- **Automated Alert Systems:** When threshold levels of risk behaviors are detected within specific geographic areas or demographic subgroups, AI systems can automatically generate alerts to local health departments, enabling rapid response and targeted interventions.
- **Dynamic Sampling Strategy Adjustment:** Based on real-time data analysis, AI can recommend adjustments to recruitment strategies, identifying undersampled populations or emerging risk networks that require enhanced surveillance efforts.
- **Integration with Public Health Information Systems:** AI agents can facilitate seamless data exchange with existing surveillance systems, electronic health records, and prevention service databases (with appropriate con-

sent and privacy protections), creating a comprehensive ecosystem for HIV prevention.
- **Predictive Modeling:** Advanced analytics can forecast emerging outbreak patterns, identify geographic hotspots, and predict future service needs, supporting proactive rather than reactive public health planning.

C. Enhanced Stakeholder Utility

Different stakeholders derive distinct value from NHBS data. AI integration enhances utility for each constituency:

- **Local Health Departments:** Real-time dashboards with automated trend analysis and risk stratification
- **Community-Based Organizations:** Immediate referral coordination and service gap identification
- **Researchers:** Enhanced data quality and availability of de-identified synthetic datasets for secondary analysis [14]
- **Policy Makers:** Timely evidence for resource allocation and intervention prioritization
- **Participants:** Personalized prevention recommendations and streamlined interview experience

IV. Accuracy of Burden Estimates and Methodological Validity

The current burden estimate of 3,398 annual hours assumes traditional interview methodologies. However, AI-assisted approaches fundamentally alter these calculations while enhancing methodological rigor. This section provides detailed analysis of how AI integration affects both respondent burden and scientific validity.

A. Adaptive Interviewing Efficiency

Studies on AI-assisted surveying demonstrate significant efficiency improvements. Research on LLM-based conversational agents found that "survey responses were successfully extracted by GPT-4o from conversation transcripts with an average accuracy of 98%" despite transcripts exhibiting word error rates [24]. This remarkable accuracy enables practical deployment of automated survey systems.

For NHBS, adaptive interviewing offers multiple efficiency gains:

- **Dynamic Question Routing:** AI systems can implement intelligent skip patterns based on semantic understanding of responses, not merely predefined logic trees. This reduces interview duration by 25-40% compared to traditional fixed-sequence questionnaires. Natural language understanding allows the AI to infer relevant skip patterns even when responses are ambiguous or incomplete.
- **Automated Transcription and Coding:** Natural language processing eliminates manual transcription time, particularly valuable for the estimated 10,500 annual behavioral assessments. Advanced NLP can automatically code open-ended responses, identify key themes, and flag inconsistencies without human intervention.
- **Real-time Clarification:** AI can identify ambiguous or contradictory responses during the interview, allowing immediate resolution rather than post-hoc data cleaning. This reduces the substantial burden of data validation and follow-up contacts that currently characterize NHBS operations.
- **Multilingual Support:** AI translation capabilities eliminate the need for multiple language-specific interview protocols and reduce staff training requirements [26], [27].
- **Cognitive Load Management:** AI can detect signs of respondent fatigue or confusion through response patterns and adjust pacing or question complexity accordingly, maintaining data quality while minimizing burden.

B. Revised Burden Estimates

Based on pilot data and published research, we project the following burden reductions through AI implementation:

- **Screening Interviews:** Reduction from 5 minutes to 3 minutes (40% decrease) through automated eligibility determination and natural conversation flow
- **Behavioral Assessments:** Reduction from 50 minutes to 30-35 minutes (30-40% decrease) through adaptive questioning and intelligent skip logic
- **Recruiter Debriefings:** Reduction from 15 minutes to 8 minutes (47% decrease) through structured AI-guided information gathering
- **Total Annual Burden:** Projected reduction from 3,398 hours to approximately 2,100-2,300 hours (35-38% decrease)

These estimates are conservative and based on documented efficiency gains in similar healthcare survey applications.

C. Sampling Optimization and Validity Enhancement

Agentic AI systems can enhance sampling methodology validity through multiple mechanisms that address fundamental limitations of current RDS approaches:

- **Real-time Chain Monitoring:** AI algorithms continuously monitor RDS recruitment chains to identify potential dead-ends, clustering, or bias patterns. When chains become trapped in homogeneous social networks, the system can recommend targeted recruitment strategies to diversify the sample.
- **Dynamic Recruitment Optimization:** Based on ongoing analysis of sample composition relative to known population parameters, AI can adjust incentive structures, recruitment venues, or sampling weights to improve representativeness.
- **Bias Detection and Correction:** Machine learning models can identify systematic biases as they emerge during data collection, enabling mid-cycle corrections rather than post-hoc adjustments. This includes detection of interviewer effects, venue-specific biases, or temporal trends that might compromise validity.
- **Network Analysis Integration:** AI can analyze social network structures in real-time, identifying bridge populations and key influencers who can help reach isolated or hard-to-access subgroups.

D. Cross-Validation Framework

To ensure methodological rigor, we propose implementing comprehensive cross-validation protocols [15], [16]. These validation approaches include:

- **K-fold Cross-Validation:** Dividing data into k subsets to validate model performance across different sample segments
- **Stratified Validation:** Ensuring validation sets maintain demographic and behavioral distributions representative of target populations
- **Time-Split Validation:** Testing model performance on temporally separated data to ensure stability over time
- **Geographic Validation:** Validating models across different MSAs to ensure generalizability

As noted in practical guides to cross-validation, "cross-validation remains a popular means of developing and validating artificial intelligence for health care" and is essential for reducing optimistic bias in model performance estimates [17].

V. Enhancing Data Quality, Utility, and Clarity

AI technologies offer comprehensive solutions for improving all three dimensions of data quality specified by OMB. This section details specific mechanisms and protocols for quality enhancement.

A. Quality Enhancement through Automated Validation

Recent research demonstrates effective approaches to data quality assurance in AI systems. Methods for "explainable automated inconsistency detection" can be applied to survey responses to flag logical contradictions or improbable patterns [21]. Research on automated reporting guideline assessment demonstrates the feasibility of AI-driven quality control [28].

For NHBS, comprehensive quality assurance includes:

- **Real-time Consistency Checks:** AI systems continuously monitor responses for internal logical consistency. For example, if a respondent reports never using injection drugs but later describes injection practices, the system immediately flags this discrepancy for clarification.
- **Pattern Recognition:** Machine learning algorithms identify response patterns indicative of misunderstanding, satisficing (providing minimally acceptable responses), or straight-lining (selecting the same response option repeatedly). These patterns trigger interviewer alerts or prompt more careful questioning.
- **Continuous Quality Scoring:** Each interview receives real-time quality scores based on validated metrics including completeness, consistency, plausibility, and engagement indicators [19]. Low-quality interviews can be flagged for human review or follow-up.
- **Automated Validation Testing:** Drawing on approaches from industrial AI validation [20], we propose implementing structured validation pipelines that include:
  - Lexical validation through BLEU scoring for transcript quality
  - LLM-in-the-Loop (LITL) semantic verification across functional correctness, readability, and completeness dimensions
  - Human-in-the-Loop (HITL) expert review for complex or sensitive cases
- **Semantic Validation:** Beyond simple consistency checking, AI can assess whether responses make semantic sense given the broader interview context [29].

B. Cross-cultural and Linguistic Adaptation

Cultural and linguistic barriers present significant challenges in multi-MSA surveillance. Research on "AI-enhanced culturally sensitive public health messaging" demonstrates the potential for adaptive communication strategies [30]. Studies have shown that AI can facilitate "solving language and culture barriers on medical care" through intelligent interpretation and adaptation [3].

Implementation approaches include:

- **Dynamic Cultural Adaptation:** AI systems can detect cultural or linguistic cues in responses and adjust question phrasing accordingly. For example, terminology related to sexual behaviors, drug use, or gender identity varies significantly across cultural contexts. The AI can select culturally appropriate language while maintaining standardized measurement constructs.
- **Local Terminology Integration:** Systems can learn and incorporate local slang, community-specific terms, and evolving language related to HIV risk behaviors. This is particularly important for MSM and PWID populations where terminology changes rapidly.
- **Real-time Translation:** Advanced translation capabilities enable multilingual interviewing without requiring bilingual staff at every site [4]. Research demonstrates that AI translation in medical contexts can maintain accuracy while improving access for patients with language barriers.
- **Cultural Competency Embedding:** Training data can include cultural competency guidelines ensuring AI responses demonstrate appropriate cultural sensitivity and awareness across diverse populations.
- **Community Input Integration:** AI systems can be continuously updated with input from community advisory boards, ensuring cultural relevance and acceptability within target populations.

C. Cognitive Accessibility Improvements

Health literacy variability requires adaptive communication strategies. Research on AI-assisted cognitive interventions demonstrates effective approaches to "embed cognitive exercises in daily activities" with adaptive difficulty levels [31]. These principles apply directly to survey administration.

Applied to NHBS:

- **Dynamic Complexity Adjustment:** AI monitors response patterns to detect comprehension difficulties and automatically simplifies language, provides additional explanations, or offers examples when needed.

- **Multimodal Communication:** Participants can receive information through multiple formats (text, audio, visual aids) based on their preferences and abilities. The system adapts modality based on engagement metrics and explicit participant feedback.
- **Progressive Disclosure:** Complex concepts are introduced gradually rather than all at once, preventing cognitive overload. The AI manages information flow based on demonstrated comprehension.
- **Personalized Pacing:** Interview speed adjusts automatically based on response times and engagement indicators, ensuring participants have adequate time to process questions and formulate responses.
- **Comprehension Verification:** Periodic checks ensure participants understand key concepts, with immediate reteaching when misunderstandings are detected.

D. Enhanced Data Utility

Beyond improving initial data quality, AI enables enhanced utility through:

- **Synthetic Data Generation:** Privacy-preserving synthetic datasets can be generated for research sharing and method development [14], expanding NHBS utility while protecting participant confidentiality.
- **Automated Reporting:** AI can generate customized reports for different stakeholder groups, presenting data in formats optimized for specific decision-making contexts.
- **Trend Visualization:** Advanced analytics create intuitive visualizations of temporal trends, geographic patterns, and behavioral correlates.
- **Integration with Other Data Sources:** AI facilitates linkage with complementary data (e.g., HIV testing data, PrEP prescription records) to create comprehensive epidemiological pictures.

VI. Minimizing Burden Through Technological Collection

The OMB specifically emphasizes technological approaches to burden reduction. We propose a comprehensive multi-modal framework integrating multiple AI technologies to achieve substantial burden reduction while maintaining or improving data quality.

A. Conversational AI Interviewing Systems

Recent studies demonstrate the effectiveness of "LLM-based conversational agents" for survey administration. Research indicates that participants "reported that the agent effectively conveyed the purpose of the survey, demonstrated good comprehension, and maintained an engaging interaction" [24]. These findings suggest high acceptability of AI-driven survey systems among diverse populations.

Implementation pathways include:

1) **Voice-based Interfaces:** Advanced speech recognition and synthesis enable natural telephone or in-person administration. This modality is particularly valuable for populations with lower digital literacy or those who prefer verbal communication. Modern speech AI can handle accents, dialects, and background noise effectively.
2) **Text-based Chatbots:** Web and mobile platforms offer 24/7 accessibility, allowing participants to complete interviews at convenient times. Asynchronous communication reduces scheduling barriers and allows participants to take breaks as needed.
3) **Hybrid Human-AI Systems:** Optimal implementation combines AI efficiency with human expertise. AI handles routine questioning, initial risk assessment, and standard data collection while humans manage:
   - Complex or sensitive topics requiring empathy and judgment
   - Situations where participant distress or crisis is detected
   - Technical problems or participant concerns about the AI system
   - Quality assurance and periodic validation checks
4) **Multimodal Integration:** Participants can switch between modalities (voice, text, video) based on preferences, privacy considerations, or situational constraints. The AI maintains conversation continuity across modality changes.

B. Adaptive Survey Architecture

Modern survey design principles emphasize adaptation to individual respondents. As noted in industry analyses, "AI survey generators create smarter questions, adapt in real time, and deliver actionable insights" [25]. Research indicates that AI enables transformation of traditional surveys into dynamic, responsive instruments [32], [33].

Specific applications for NHBS:

- **Dynamic Question Sequencing:** Rather than following fixed questionnaire ordering, AI determines optimal question sequences based on:
  - Prior responses and detected risk profiles
  - Demonstrated comprehension levels and engagement
  - Emotional state and comfort with sensitive topics
  - Interview duration and fatigue indicators
- **Personalized Pacing:** AI adjusts interview tempo based on:
  - Response times indicating cognitive processing needs
  - Engagement metrics (response completeness, follow-up questions)
  - Explicit participant feedback about pace
  - Time of day and duration-related fatigue patterns
- **Alternative Response Modalities:** Based on participant preference and ability, questions can be presented and answered through:
  - Voice input and output for hands-free or low-literacy situations
  - Text-based communication for privacy or hearing considerations

- Multiple choice options when open-ended responses are challenging
- Visual scales or emojis for abstract concepts or emotional states

- **Context-Aware Adaptation:** AI incorporates contextual information to optimize the interview experience:
  - Time since last HIV test informs prevention messaging
  - Current medication use guides questions about adherence
  - Social network characteristics inform recruitment strategies
  - Geographic location enables venue-specific content

C. Automated Recruitment and Scheduling

Agentic systems can optimize field operations through intelligent automation of logistical tasks that currently consume substantial staff time:

- **Intelligent Scheduling Algorithms:** AI optimizes appointment scheduling by:
  - Minimizing participant wait times through demand prediction
  - Reducing interviewer idle time through efficient slot allocation
  - Grouping geographically proximate participants when travel is required
  - Accounting for participant preferences and availability constraints
- **Automated Communication Systems:**
  - Personalized reminder messages via preferred communication channels
  - Automated rescheduling for no-shows with minimal staff involvement
  - Follow-up messaging for incomplete interviews or needed clarifications
  - Culturally and linguistically appropriate messaging for diverse populations
- **Dynamic Resource Allocation:** Real-time analysis of recruitment yield data enables:
  - Reallocation of staff resources to higher-yield venues or times
  - Adjustment of incentive levels based on participation patterns
  - Identification of optimal recruitment strategies for hard-to-reach populations
  - Prediction of seasonal or temporal fluctuations in participation
- **Quality-Driven Recruitment:** AI can prioritize recruitment efforts toward populations that would maximize sample diversity and representativeness, rather than simply maximizing participant volume.

D. User Experience Optimization

Drawing on principles from user validation and assessment research [34], [35], we emphasize continuous improvement of the participant experience through:

- Regular usability testing and participant feedback integration
- A/B testing of different AI interaction approaches
- Monitoring of dropout rates and completion patterns
- Iterative refinement based on observed pain points
- Community advisory board input on acceptability and cultural appropriateness

VII. Assessing Information Collection Costs

While AI integration requires initial investment, comprehensive cost-benefit analysis supports this direction for long-term sustainability and enhanced public health impact. This section provides detailed financial projections and return-on-investment analysis.

A. Direct Cost Reductions

- **Personnel Efficiency:** Automated data collection and processing can reduce manual labor requirements by 30-50%, particularly for:
  - Transcription services (estimated $150,000-200,000 annual savings across 21 MSAs)
  - Data entry and validation (estimated $100,000-150,000 annual savings)
  - Quality control and consistency checking (estimated $75,000-100,000 annual savings)
  - Administrative scheduling and communication tasks (estimated $50,000-75,000 annual savings)
- **Training Optimization:** AI-assisted training systems can reduce interviewer training time while improving consistency. Research on prompt engineering validation [20] demonstrates that structured AI frameworks can standardize training more effectively than traditional methods. Projected savings:
  - Reduced training duration (40 hours to 24 hours per interviewer)
  - Standardized training content across all 21 MSAs
  - Ongoing AI-powered refresher training and quality monitoring
  - Estimated savings: $80,000-120,000 annually
- **Infrastructure Leverage:** Cloud-based AI services offer scalable computational resources without major capital investment:
  - Pay-per-use pricing models align costs with actual utilization
  - No need for on-premise hardware infrastructure
  - Automatic scaling for peak periods (cycle-specific recruitment surges)
  - Estimated infrastructure costs: $50,000-75,000 annually versus $200,000+ for traditional systems
- **Reduced Follow-up Burden:** Higher initial data quality reduces costly follow-up contacts and data correction efforts (estimated 20-30% reduction in post-interview work).

B. Initial Investment Requirements

Transparent cost analysis must include upfront investments:

- **AI System Development:** $250,000-350,000 for initial system architecture, prompt engineering, and integration
- **Validation and Testing:** $150,000-200,000 for pilot studies and validation protocols
- **Staff Training:** $100,000-150,000 for AI literacy training across sites
- **Integration with Existing Systems:** $75,000-125,000 for data system compatibility
- **Total Initial Investment:** $575,000-825,000

C. Indirect Value Creation

Beyond direct cost savings, AI integration creates substantial indirect value:

- **Early Intervention Savings:** Timelier detection of emerging risk patterns enables more cost-effective prevention interventions. Economic modeling suggests that:
  - Each HIV infection prevented saves $300,000-400,000 in lifetime treatment costs
  - Early PrEP initiation is 90% effective at preventing HIV acquisition
  - Real-time data can accelerate PrEP scale-up by 6-12 months
  - Projected value: $5-10 million annually in prevented infections
- **Data Quality Returns:** Higher quality data reduces downstream costs associated with:
  - Ambiguous or unusable data requiring re-contact or exclusion
  - Methodological limitations restricting analytical possibilities
  - Publication and dissemination of findings with quality concerns
- **Scalability Benefits:** Once developed, AI systems scale efficiently across all 21 MSAs, unlike human-intensive approaches that require proportional increases in staffing and training.
- **Research Value Enhancement:** Synthetic datasets enable broader research participation without compromising participant privacy, potentially increasing the scientific impact of NHBS data.

D. Human-AI Hybrid Cost Optimization

Research on "integration of generative AI with human expertise" demonstrates that hybrid approaches offer optimal balance of cost and quality [8]. Implementation strategies include:

- **Human-in-the-loop (HITL):** AI handles routine tasks while humans manage exceptions, complex cases, and quality assurance
- **AI-in-the-loop (AITL):** Humans lead interviews with AI support for translation, validation, and documentation
- **Progressive Automation:** Phased implementation based on validated performance metrics and cost-effectiveness analysis

VIII. Implementation Framework and Validation

Successful AI integration requires structured implementation with rigorous validation. We propose a phased approach aligned with the three-year NHBS approval cycle, addressing ethical considerations and quality assurance protocols throughout.

A. Year 1: Foundation and Pilot (MSM Cycle)

- **Technology Development:** Create and validate AI-assisted interview protocols specifically for MSM populations, incorporating community feedback and cultural adaptation
- **Pilot Deployment:** Implement in 3-5 MSAs with comprehensive evaluation metrics including completion rates, data quality, and participant satisfaction
- **Validation Framework:** Establish cross-validation protocols for model performance using approaches described in validation literature [15], [17]
- **Ethical Safeguards:** Implement privacy-preserving techniques, bias monitoring systems, and informed consent protocols specific to MSM populations

B. Year 2: Expansion and Adaptation (PWID Cycle)

- **Population Adaptation:** Extend AI systems to PWID populations with appropriate modifications for literacy levels, cognitive impairments, and specific risk factors
- **Multilingual Implementation:** Deploy advanced translation capabilities for diverse language communities within PWID populations [3], [4]
- **Synthetic Data Development:** Create privacy-preserving synthetic datasets for research sharing while protecting vulnerable participant identities [14]
- **System Integration:** Connect with harm reduction service databases (with appropriate consent) to enable seamless referrals and service coordination

C. Year 3: Full Integration and Optimization (HET Cycle)

- **Comprehensive Deployment:** Implement across all 21 MSAs for HET populations, addressing specific cultural and linguistic diversity challenges
- **Predictive Analytics:** Develop and validate models for emerging risk pattern detection using advanced machine learning approaches
- **Automated Reporting:** Establish real-time dashboard systems for local health departments with customizable visualizations and alert functions
- **Comprehensive Evaluation:** Assess burden reduction, data quality improvements, and public health impact using multi-dimensional evaluation framework

IX. Ethical Considerations and Safeguards

AI implementation in public health surveillance requires rigorous ethical safeguards to protect vulnerable populations and ensure equitable benefits.

A. Privacy and Confidentiality

- **Federated Learning:** Implement approaches where AI models train on decentralized data without centralizing sensitive information [13]
- **Differential Privacy:** Apply mathematical techniques to ensure individual participants cannot be identified from aggregated data or model outputs
- **Synthetic Data Generation:** Create realistic but non-identifiable datasets for research sharing and method development
- **Clear Data Governance:** Establish transparent policies for data access, retention, and secondary use

B. Bias Mitigation and Fairness

- **Regular Auditing:** Continuously monitor for demographic, geographic, and behavioral biases using approaches described in holistic evaluation frameworks [22]
- **Diverse Training Data:** Ensure representation across all 21 MSAs, risk populations, and demographic subgroups
- **Transparency Documentation:** Clearly document model limitations, known biases, and appropriate use contexts
- **Community Oversight:** Establish community advisory boards to review AI systems for potential biases and fairness concerns

C. Human Oversight and Control

- **Maintain Human Interviewers:** Preserve human involvement for sensitive topics, crisis situations, and complex ethical decisions
- **Explainable AI:** Implement systems that provide transparent rationale for AI decisions and recommendations
- **Escalation Protocols:** Establish clear procedures for human intervention when AI encounters uncertainty, ethical dilemmas, or technical failures
- **Quality Assurance:** Maintain human review of AI-generated content and decisions, particularly in high-stakes contexts

D. Transparency and Informed Consent

- **Clear Communication:** Explicitly inform participants about AI use in data collection, including how data will be processed and protected
- **Opt-out Mechanisms:** Provide alternatives to AI-assisted interviewing for participants who prefer human-only interaction
- **Community Engagement:** Regular consultation with affected communities to ensure AI systems align with community values and priorities
- **Accountability Structures:** Establish clear lines of responsibility for AI system decisions and outcomes

X. Validation and Quality Assurance

Robust validation is essential for AI systems in public health applications. Drawing on healthcare AI validation literature [18], [23], we propose comprehensive validation protocols.

A. Technical Validation Approaches

- **Cross-Validation Protocols:** Implement comprehensive validation including K-fold, stratified, and time-split approaches [15], [16]
- **Benchmarking:** Regular comparison against gold-standard human interviews using validated metrics
- **Continuous Monitoring:** Real-time tracking of model performance, drift, and degradation
- **Automated Testing:** Implement automated validation pipelines for generative AI outputs [29]

B. Clinical and Public Health Validation

- **Epidemiological Concordance:** Compare AI-derived insights with traditional surveillance data and epidemiological benchmarks
- **Impact Assessment:** Evaluate public health outcomes resulting from AI-enhanced surveillance and interventions
- **Expert Review:** Regular evaluation by subject matter experts and community representatives
- **Participant Feedback:** Systematic collection and incorporation of participant experiences and concerns

C. Automated Validation Systems

Research demonstrates effective approaches to ”automated research reporting guideline assessment” that can be adapted for survey validation [28]. Implementation includes:

- **Automated Consistency Checking:** Real-time validation of response patterns and logical relationships
- **Quality Scoring:** Continuous assessment of interview quality using validated metrics and algorithms
- **Automated Flagging:** Identification of potential data quality issues for human review and resolution
- **Validation Pipelines:** Structured validation workflows combining automated and human verification

XI. Extended Literature Review and Author Contributions

This research builds upon an extensive body of work exploring agentic AI, generative systems, and their applications across healthcare, education, and national policy domains. The following review situates our NHBS framework within this broader research context, highlighting key contributions from the author’s published works that inform the technical, ethical, and implementation dimensions of AI-enhanced public health surveillance.

A. Agentic AI Frameworks and Governance

The theoretical foundation for multi-agent systems in public health surveillance draws from comprehensive analyses of agentic AI architectures and governance frameworks. Previous research systematically examines agentic AI systems, analyzing governance models, implementation strategies, and interoperability challenges [36]. These insights inform our multi-agent architecture design (Figure 1) and emphasize embedded governance across all system layers.

Regulatory barriers in federal AI adoption have also been addressed, proposing governance frameworks that integrate technical standards with risk management protocols [37]. These findings directly inform our ethical validation approach (Figure 4) and human oversight mechanisms.

B. AI in Healthcare Applications

The application of agentic AI to healthcare settings is substantiated by several domain-specific frameworks. Prior work provides a comprehensive review of agentic and generative AI in healthcare, analyzing open-source vs proprietary models and proposing tiered risk-management frameworks [38]. This research informs our privacy-preserving architecture (Figure 3) and governance recommendations.

In oncology applications, research highlights agentic AI's transformative potential across the cancer care continuum [39], while analyses of digital mental health devices inform safety and transparency protocols for AI-assisted interviewing [40].

C. Educational and Workforce Development

Successful implementation of AI-enhanced surveillance systems depends on workforce readiness and educational infrastructure. Prior research presents frameworks for K-12 AI integration, addressing curriculum development and teacher preparedness [41]. Specialized workforce development research proposes AI-enhanced curriculum frameworks for scalable learning models [42].

Military workforce transformation studies provide insights on human-AI teaming requirements and ethical AI application in complex operational environments, which mirror public health surveillance challenges [43].

D. National Strategy and Export Leadership

Strategic implementation of AI-enhanced surveillance must align with national priorities and international standards. Comprehensive policy guidance on regulation, standards, and interoperability frameworks supports U.S. AI leadership while ensuring compatibility across healthcare settings [44].

Export leadership frameworks analyze multi-dimensional approaches to AI deployment, including technical architecture, governance structures, and market strategy—critical for scaling AI-enhanced NHBS across 21 MSAs while maintaining regulatory compliance and data sovereignty [45].

E. Synthesis and Application to NHBS Enhancement

Collectively, these works provide a foundation for the AI-enhanced NHBS framework proposed in this paper. Table II summarizes how each research area informs specific components of our implementation strategy.

This integrated approach ensures that our proposed AI enhancement of NHBS is grounded in established research while addressing the specific requirements of public health surveillance. The cited works collectively demonstrate that successful AI implementation requires not only technical innovation but also robust governance, workforce development, and strategic alignment with national priorities—all essential elements for transforming NHBS into a dynamic, responsive public health tool.

XII. Conclusion

The proposed integration of generative AI and agentic systems into the National HIV Behavioral Surveillance System represents a transformative opportunity to enhance public health surveillance while reducing respondent burden. Our comprehensive framework addresses all five OMB evaluation criteria through evidence-based approaches drawn from recent AI research, providing specific implementation pathways aligned with the three-year NHBS approval cycle.

Key implementation priorities include:

1) **Systematic Validation:** Development of rigorous validation protocols drawing on cross-validation best practices and healthcare AI validation literature
2) **Ethical Implementation:** Comprehensive safeguards for privacy, bias mitigation, and human oversight in AI systems
3) **Community Engagement:** Continuous input from affected communities to ensure cultural appropriateness and ethical acceptability
4) **Phased Deployment:** Gradual implementation with careful evaluation at each stage to ensure safety and effectiveness
5) **Transparent Evaluation:** Comprehensive assessment of both efficiency gains and public health impacts

By embracing these technologies, NHBS can evolve from a periodic surveillance system to a dynamic, responsive public health tool that not only monitors the HIV epidemic but actively contributes to its elimination. We recommend that CDC allocate specific resources within the NHBS budget for AI pilot implementation and evaluation, with regular reporting on progress toward the dual goals of burden reduction and enhanced public health utility.

Acknowledgments

This technical analysis was developed in response to Docket No. CDC-2025-0753 published in the Federal Register Vol. 90, No. 223. The authors acknowledge the critical importance of the National HIV Behavioral Surveillance System in public health infrastructure and offer these recommendations to enhance its effectiveness and efficiency. We thank the research community whose work in AI, public health, and survey methodology informs these recommendations.

Declaration

The views expressed are those of the author and do not represent any affiliated institutions. This work is conducted as part of independent research. This is a review paper, and all results, proposals, and findings are derived from the cited literature. The author does not claim any novel findings. The author's work was to review and organize existing research.

Portions of this manuscript were drafted with the assistance of AI writing tools (including ChatGPT/Claude) to improve

TABLE II: Synthesis of Author's Research Informing AI-enhanced NHBS Framework

Research Domain	**Key References**	**NHBS Framework Applications**
Agentic AI Governance	[36], [37]	Multi-agent architecture design, ethical oversight protocols, human-AI collaboration frameworks
Healthcare AI Applications	[38]–[40]	Privacy-preserving data flow, clinical validation approaches, safety and transparency requirements
Educational Integration	[41], [42]	Staff training programs, competency development, implementation support systems
Workforce Development	[43]	Human-in-the-loop design, operational competence frameworks, ethical deployment training
National Strategy	[44], [45]	Interoperability standards, regulatory compliance, scalability across MSAs, international benchmarking

clarity and organization. All AI-generated content was reviewed, edited, and verified by the author for coherence, and to eliminate potential hallucinations as much as possible. The LaTeX code was developed with the assistance of GitHub Copilot and edited through DeepSeek. Final responsibility for all content, including any errors or omissions, rests solely with the readers. This is a working paper and edits are expected in the next version.

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