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Review article

The role of artificial intelligence in blood-borne virus opt-out testing in emergency departments

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ABSTRACT

Introduction: Blood-borne viruses (BBVs) such as HIV, hepatitis B, and hepatitis C continue to pose serious public health concerns, particularly within emergency departments (EDs), where patient volume and turnover are high. While opt-out testing strategies, where individuals are tested unless they specifically decline, have shown effectiveness in increasing diagnosis rates, their adoption in EDs is limited by challenges such as inefficient workflows, data fragmentation, and suboptimal patient engagement.
Aim: This narrative review aims to explore the application of Artificial Intelligence (AI) in enhancing BBV opt-out testing in EDs, focusing on how AI can address current operational and clinical challenges while supporting ethical and equitable implementation.
Method: A structured narrative review approach was used following established guidelines. We searched PubMed, EMBASE, Web of Science, and grey literature from 2010 to 2024 using terms related to AI, blood-borne viruses, opt-out testing, and emergency departments. A total of 32 articles were included in the final synthesis.
Results: AI demonstrates theoretical potential with limited BBV-specific empirical evidence in improving BBV testing outcomes through automated patient identification and risk stratification using electronic health records. Evidence from broader healthcare AI applications suggests workflow improvements may be possible through automated test ordering, real-time alerts, and adaptive scheduling systems. Data analysis tools have shown promise in other healthcare contexts for accurate test result interpretation and epidemiological trend identification. AI-driven patient communication tools such as chatbots and mobile apps show potential to enhance patient understanding and reduce opt-out rates. Follow-up and continuity of care could potentially be strengthened via automated notifications and predictive adherence models.
Conclusion: AI offers potential opportunities to improve the scalability, efficiency, and equity of BBV opt-out testing in EDs. However, successful integration depends on addressing ethical issues, algorithmic bias, and system interoperability, supported by interdisciplinary collaboration and continuous evaluation. Further research with BBV-specific evidence is urgently needed to validate these theoretical applications.

1. Introduction

Blood-borne viruses (BBVs) such as HIV, hepatitis B, and hepatitis C are significant global health challenges, contributing to high morbidity and mortality rates [1]. Early detection and treatment are vital for managing these diseases, reducing their transmission, and improving

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patient outcomes. Emergency departments (EDs) provide a unique opportunity to address these challenges as they serve large, diverse patient populations [2,3]. Adopting opt-out testing for BBVs, where patients are tested unless they actively decline, has emerged as a key strategy to improve detection rates [4]. This approach normalises testing, reduces stigma, and ensures broader coverage across populations that might be overlooked. However, despite its promise, operational challenges often hinder its practical implementation in EDs, limiting its full potential.

The fast-paced environment of EDs poses significant logistical challenges to successfully integrating BBV opt-out testing programmes [5]. Identifying eligible patients promptly, integrating testing workflows with existing systems, and managing the large volumes of data generated are significant barriers. Moreover, ED staff are frequently overburdened, with little time to ensure consistent implementation of screening protocols [6]. Fragmented systems and limited resources further complicate follow-up care for patients who test positive, leaving gaps in the continuity of care. These challenges highlight the need for innovative approaches to streamline operations, enhance efficiency, and ensure the sustainability of opt-out testing programmes.

Artificial Intelligence (AI) offers potential solutions to address these operational hurdles [7]. AI algorithms can leverage electronic health records (EHRs) to identify patients eligible for testing based on demographic, clinical, and risk-based criteria [8]. Predictive analytics may prioritise high-risk individuals, enabling targeted testing efforts that could maximise impact. Furthermore, AI-driven systems have the potential to automate infectious disease testing workflows, reducing reliance on manual processes and minimising errors [9,10]. AI could alleviate the administrative burden on clinical staff and enable more consistent and effective implementation of BBV testing in EDs, even in high-pressure environments.

In addition to operational benefits, AI may significantly enhance patient engagement and outcomes during microbiology diagnosis [8]. Natural language processing (NLP)-powered tools, such as chatbots, could communicate effectively with patients, addressing their concerns and providing clear explanations about the diagnostic analysis [11,12]. AI systems may also streamline follow-up care by automating reminders for positive cases of infectious diseases and connecting patients to appropriate healthcare providers [13,14]. Predictive models could identify barriers to follow-up, enabling targeted interventions to improve continuity of care. Moreover, AI analytics may provide actionable insights from testing data, supporting public health authorities in refining disease control and prevention strategies [15,16].

While AI has theoretical potential for revolutionising BBV opt-out testing in EDs, its integration faces significant challenges. Data security and patient privacy are critical, particularly given the sensitive nature of BBV-related information [17]. AI models must also address algorithmic biases that could exacerbate care inequities [18,19]. Integrating AI systems with existing EHR platforms and ED workflows requires significant technical expertise and financial investment. Real-world implementation barriers include staff training requirements, system interoperability issues, cost implications, resistance from clinical personnel, and IT infrastructure limitations in public hospitals. However, these challenges may be mitigated with thoughtful design, robust governance frameworks, and collaboration among technologists, clinicians, and policymakers. The effective use of AI in BBV opt-out testing represents a potential opportunity to enhance public health outcomes and address one of our most pressing global health challenges [20,21].

The rationale for this narrative review stems from the critical need to examine both the theoretical potential and practical challenges of AI implementation in BBV opt-out testing programmes. While AI applications in broader healthcare contexts show promise, BBV-specific evidence remains limited, creating a gap between theoretical possibilities and clinical reality. This review aims to critically evaluate AI's current applications and future potential in optimising BBV opt-out testing in EDs, whilst acknowledging the distinction between evidence-based interventions and theoretical possibilities.

2. Methodology

This structured narrative review was conducted following established guidelines for narrative reviews in healthcare. The review aimed to synthesise current knowledge on AI applications in BBV opt-out testing whilst identifying gaps between theoretical potential and empirical evidence.

2.1. Search strategy

A comprehensive literature search was performed across multiple databases including PubMed, EMBASE, Web of Science, and Cochrane Library from January 2010 to December 2024. Search terms combined Medical Subject Headings (MeSH) and free-text terms related to: (1) artificial intelligence, machine learning, automation; (2) blood-borne viruses, HIV, hepatitis B, hepatitis C; (3) opt-out testing, routine testing, screening; (4) emergency departments, emergency medicine. Grey literature sources included government reports, policy documents, and technology reports from relevant organisations.

2.2. Inclusion and Exclusion criteria

Inclusion criteria were: (1) peer-reviewed articles, policy documents, and technical reports; (2) studies focusing on AI applications in healthcare testing, infectious disease management, or BBV-related interventions; (3) relevance to emergency department settings or acute care environments; (4) published in English language; (5) publication date from 2010 onwards.

Exclusion criteria were: (1) studies not related to BBV, infectious disease testing, or healthcare AI; (2) purely theoretical AI models without healthcare context or validation; (3) conference abstracts without full-text availability; (4) studies focusing exclusively on treatment rather than diagnosis or testing.

2.3. Study selection and data Extraction

Initial screening of titles and abstracts was performed by two independent reviewers, with disagreements resolved through discussion. As shown in Fig. 1, a total of 847 articles were initially identified through database searches and grey literature review. After removing duplicates (n = 123), 724 articles underwent title and abstract screening. Following this process, 156 articles met inclusion criteria for full-text review. Of these, 32 studies were included in the final synthesis, with the remaining articles excluded due to insufficient relevance to BBV testing in emergency care settings or lack of AI-specific content.

Given the limited number of studies specifically addressing AI in BBV opt-out testing in EDs, the review adopted a broader scope to include relevant AI applications in healthcare testing and infectious disease management to inform theoretical possibilities whilst clearly distinguishing these from BBV-specific evidence. The 32 included studies comprised a mix of BBV-specific research, broader healthcare AI applications, and policy documents relevant to emergency care settings.

3. Current challenges in BBV Opt-Out testing in emergency departments

Integrating blood-borne virus (BBV) opt-out testing into emergency departments (EDs) has proven to be a valuable public health strategy for early detection and treatment [4,22–24]. However, its implementation remains fraught with significant challenges that undermine its effectiveness. These challenges are primarily operational, relating to patient identification, data management, and follow-up processes. Addressing these issues is crucial to unlocking the full potential of BBV opt-out testing in EDs.

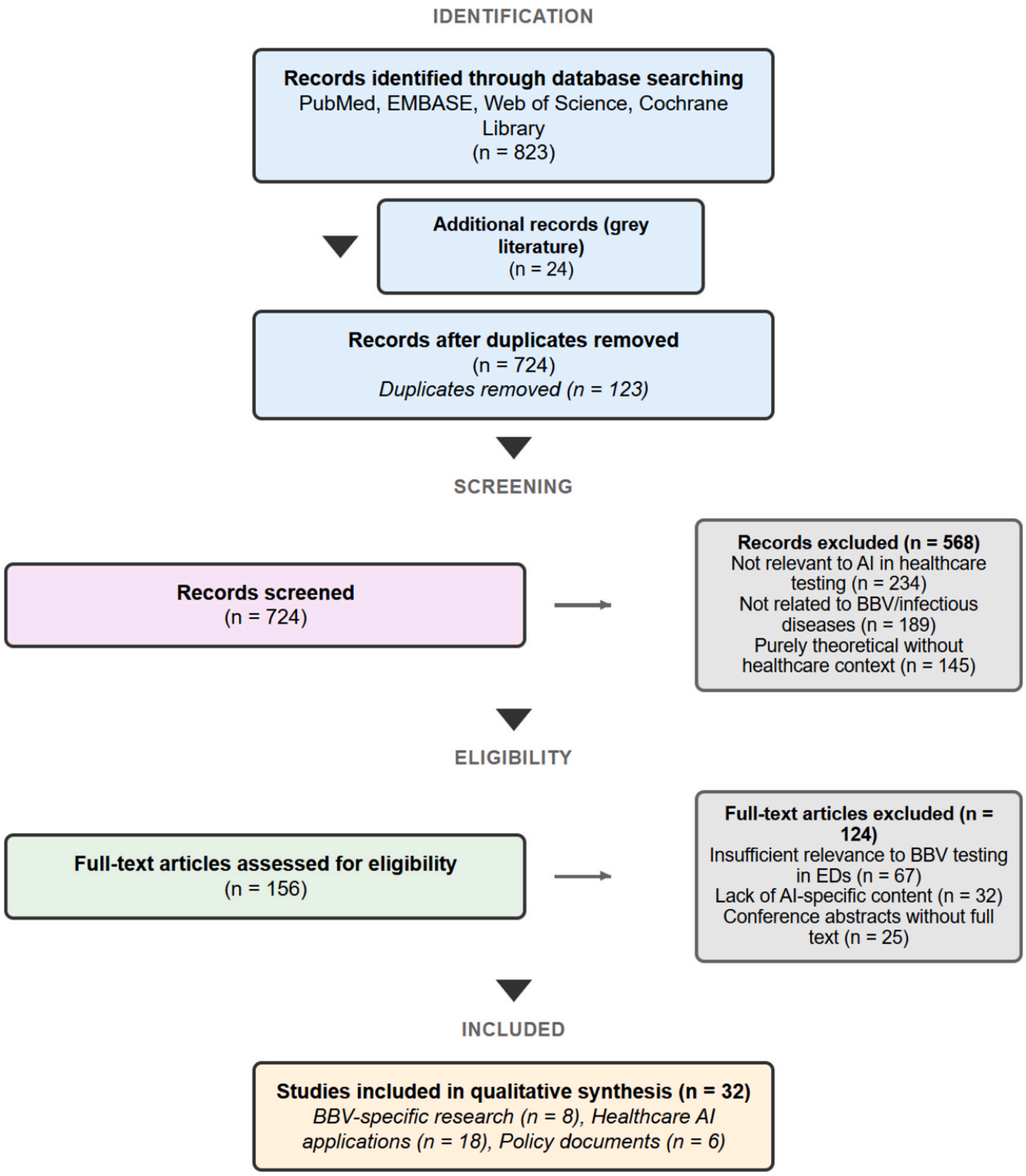

Fig. 1. PRISMA flow diagram showing the systematic selection of 32 studies from 847 initial records for this narrative review of AI applications in BBV opt-out testing in emergency departments.

3.1. Operational barriers

Emergency departments operate under immense pressure, with high patient volumes, time constraints, and the need to prioritise life-threatening conditions [5,25]. This fast-paced environment leaves little room for consistent implementation of BBV testing protocols. Healthcare workers often face competing demands, leading to inconsistencies in testing, particularly during peak hours or resource shortages. Furthermore, opt-out testing programmes require integration into existing workflows, which can disrupt standard procedures if not adequately streamlined [23,26]. Manual data collection and entry exacerbate these operational challenges. Recording patient consent, ordering tests, and documenting results are time-consuming processes prone to human error. Data handling errors reduce testing programmes' efficiency and compromise test outcomes' accuracy, potentially delaying diagnosis and treatment. These inefficiencies highlight the need for automation and robust integration solutions to optimise workflows without overburdening ED staff.

3.2. Challenges in patient identification

Accurately identifying patients eligible for BBV testing presents another significant hurdle. Many patients visiting the ED do not have complete or accessible medical histories, making it difficult to assess their risk factors for BBV infections. Social and demographic factors, such as stigma or language barriers, further complicate obtaining reliable information [25,27]. As a result, some at-risk individuals may not be appropriately flagged for testing, while others may be subjected to redundant or unnecessary screenings. Relying on clinician judgement for patient selection in non-standardised protocols can lead to variability in testing practices. Without objective and systematic criteria, identifying individuals who would most benefit from opt-out testing becomes inconsistent, resulting in missed opportunities for early detection. Addressing this challenge requires developing tools that provide reliable, data-driven insights to guide patient selection without relying solely on human judgement.

3.3. Data management and Follow-Up challenges

Implementing BBV opt-out testing in EDs generates large volumes of data, including patient records, test results, and follow-up schedules [28]. Managing this information in high-traffic EDs requires significant resources, which are often stretched thin. The lack of efficient data management systems contributes to delays in processing test results, particularly in settings that rely on manual data entry or fragmented electronic health record (EHR) systems [29]. Ineffective data management can lead to missed diagnoses, delayed interventions, and poor overall programme outcomes. Follow-up care for patients testing positive for BBVs is another critical challenge. Ensuring that patients receive timely and appropriate care after a positive result is often hindered by fragmented healthcare systems. Patients discharged from the ED may not be effectively linked to primary care providers or specialist services, leading to a gap in care continuity. For transient or underserved populations, such as those experiencing homelessness or individuals without stable healthcare access, these gaps are even more pronounced. A lack of standardised follow-up protocols and communication systems further compounds the issue, resulting in reduced adherence to treatment and public health risks associated with untreated infections.

3.4. Real-World implementation barriers

Beyond operational challenges, several real-world barriers significantly impede the implementation of BBV opt-out testing programmes in EDs. Staff training requirements represent a substantial hurdle, as healthcare workers need comprehensive education on testing protocols, consent procedures, and result management. System interoperability issues plague many healthcare settings, where legacy systems cannot easily communicate with newer testing platforms or AI-driven tools.

Cost implications pose another significant barrier, particularly for publicly funded hospitals operating under tight budgets. The initial investment in AI systems, ongoing maintenance costs, and staff training expenses can be prohibitive. Resistance from clinical personnel, often stemming from concerns about workflow disruption, increased administrative burden, or scepticism about technology integration, can undermine implementation efforts.

IT infrastructure limitations in many public hospitals further compound these challenges. Inadequate network capacity, outdated hardware, and insufficient cybersecurity measures can prevent successful deployment of AI-enhanced testing systems. These practical considerations must be addressed alongside theoretical benefits when evaluating AI applications in BBV testing programmes.

4. Applications of AI in BBV Opt-Out testing

The use of Artificial Intelligence (AI) in healthcare is showing promise across various domains, including potential applications in blood-borne virus (BBV) opt-out testing in emergency departments (EDs). AI may enhance these testing programmes' efficiency, scalability, and effectiveness by addressing key challenges such as patient identification, workflow optimisation, data management, and patient engagement [30]. This section explores how AI could potentially support BBV opt-out testing across multiple dimensions, leveraging current technological trends and innovations whilst acknowledging the limited BBV-specific empirical evidence.

4.1. Patient identification and risk stratification

AI has shown potential in transforming how patient data is analysed by integrating advanced algorithms with electronic health records (EHRs). These algorithms could process vast amounts of patient information, including demographics, medical histories, and behavioural risk factors, to identify individuals eligible for BBV testing. Unlike traditional methods, AI systems could potentially automatically and continuously scan EHRs to flag at-risk patients, ensuring no eligible individual is overlooked. This capability may be particularly valuable in EDs, where high patient volumes and time constraints often make thorough manual reviews impractical.

Predictive models, a core application of AI, are increasingly being used in other healthcare contexts to assess patient risk levels. These models leverage machine learning to identify patterns and correlations in patient data that may not be apparent through conventional analysis. While BBV-specific evidence is limited, predictive tools could theoretically flag patients with prior untested risk exposures, such as a history of injection drug use or unscreened blood transfusions, for immediate testing. By prioritising high-risk individuals, AI may enhance the precision and impact of BBV testing initiatives, ensuring that resources are directed where they are most needed [31].

Evidence from broader healthcare AI applications suggests that AI systems could leverage electronic health records (EHRs), risk stratification models, and geospatial tools to streamline eligibility screening, prioritise high-risk individuals, and address healthcare disparities, as outlined in Table 1.

4.2. Workflow optimisation

AI-driven systems show potential for reshaping workflows in EDs by automating routine tasks and optimising resource allocation. Automated testing protocols, for example, could potentially be seamlessly integrated into ED workflows to trigger testing orders based on predefined criteria. When a patient meets eligibility requirements, the system could automatically generate a test order, eliminating the need for manual input from clinicians [34]. This streamlining of processes may reduce administrative burdens, minimise delays, and ensure consistency in testing practices across shifts and staff members.

Staff allocation is another critical area where AI could potentially make a difference. The proposed AI-driven BBV opt-out testing workflow (Fig. 2) integrates seamlessly within the existing Emergency Department electronic health record (EHR) infrastructure. The EHR serves as both the primary source of patient demographic, clinical, and laboratory data and the destination for AI-generated outputs, including eligibility flags, risk scores, and automated test orders. On-premises AI modules process incoming data and interface directly with laboratory systems for test execution and result reporting. Bidirectional data flows enable continuous updates between systems, while aggregated, anonymised datasets may be securely transmitted to cloud-based analytics

Table 1
AI Applications in Patient Identification.

AI Application	Detailed Description	Impact on Emergency Departments (EDs)
Automated Eligibility Screening	AI scans EHRs for indicators like medical history and demographic factors to identify testing eligibility.	Could potentially enhance speed and accuracy, seamlessly integrating testing into busy ED workflows.
Risk Stratification [32]	Machine learning models assign risk scores based on prior diagnoses and behavioral data.	May focus on high-risk patients and improving resource allocation and detection rates.
Demographic Analysis	Analyzes socio-economic and demographic data to target underserved populations.	Could potentially reduce disparities by ensuring equitable inclusion in testing programs.
Behavioral Pattern Recognition [33]	Detects patterns like substance use or frequent ED visits linked to BBV risks.	May identify hidden risks, addressing missed diagnoses due to incomplete histories.
Epidemiological Mapping	Combines location data with healthcare statistics to pinpoint high-prevalence BBV areas.	Could support targeted public health interventions and resource allocation.

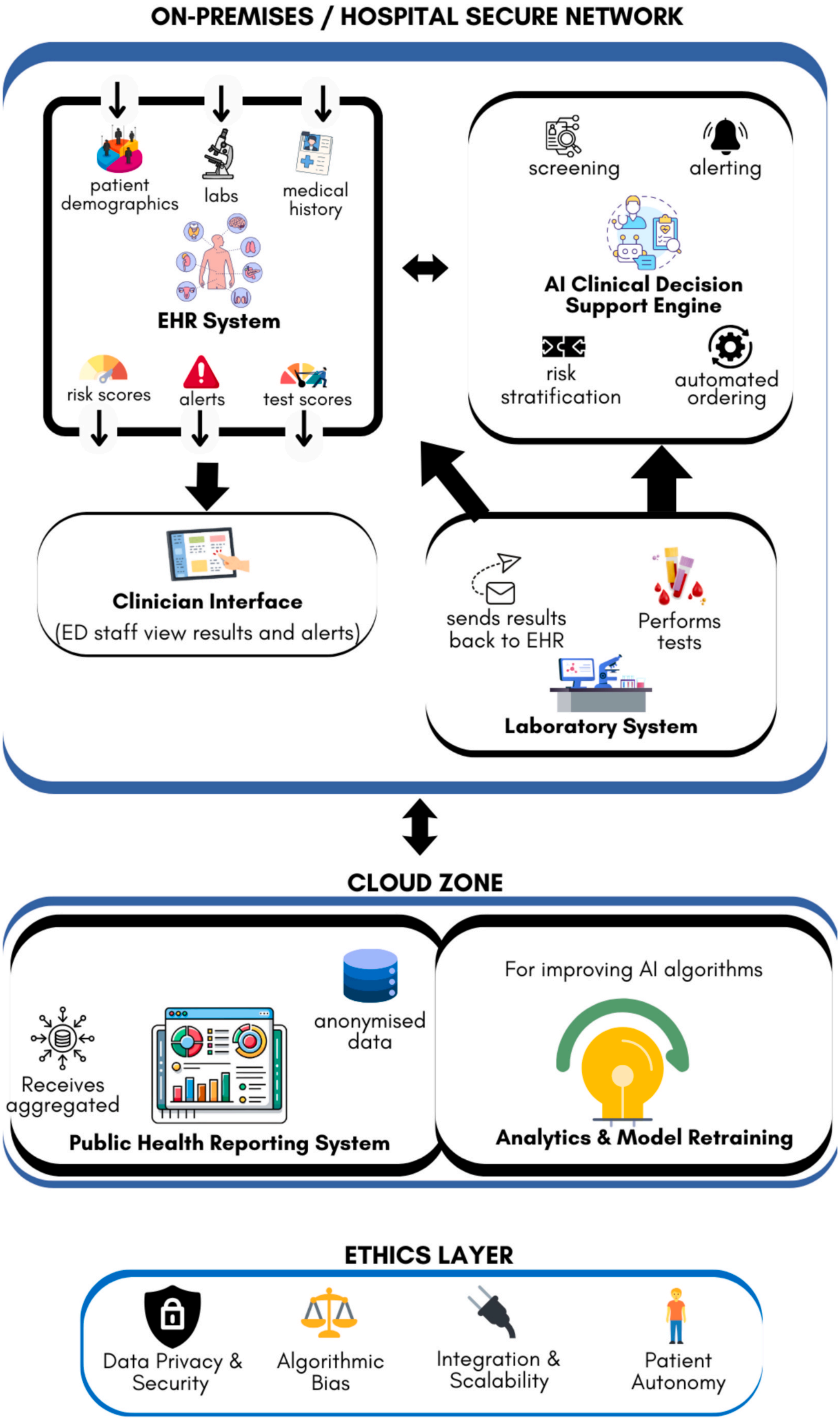

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Fig. 2. AI-driven blood-borne virus (BBV) opt-out testing workflow in the Emergency Department, showing bidirectional exchanges between the EHR system, AI Clinical Decision Support Engine, and laboratory systems. Patient demographic, clinical, and laboratory data from the EHR are processed on-premises for eligibility screening, risk stratification, and automated test ordering, with results and alerts returned to the EHR for clinician action. Aggregated, anonymised data may be securely transmitted to cloud-based systems for public health reporting and model retraining. On-premises and cloud components are separated by the hospital secure network boundary, reflecting implementation and data-governance requirements. Ethical and practical challenges, data privacy and security, algorithmic bias, integration and scalability, and patient autonomy underpin the system's design.

platforms for public health reporting and model retraining. This design reflects real-world on-premises versus cloud deployment considerations and sits within a framework of ethical safeguards concerning data privacy, algorithmic fairness, scalability, and patient autonomy.

With predictive modelling, AI tools could anticipate patient inflow and risk distribution, enabling dynamic staff allocation to high-demand areas or cases. This may ensure sufficient personnel can manage BBV testing effectively, even during peak hours. AI could also help to identify inefficiencies in resource utilisation, facilitating adjustments that improve overall operational efficiency.

Workflow optimisation, as detailed in Table 2, could potentially be achieved through automated test ordering, real-time alerts, and task prioritisation, which may minimise administrative burdens and improve resource allocation.

4.3. Data analysis and reporting

The ability of AI to rapidly analyse and interpret test results represents potential benefits in BBV testing. AI-powered systems could process large datasets with high accuracy, reducing the likelihood of errors associated with manual analysis. For example, AI might instantly categorise test results, flagging positive cases for follow-up while efficiently handling negative results. This capability could not only save time but also enhance the reliability of testing programmes. Machine learning models may extend AI's utility by identifying trends and generating actionable insights. For public health agencies, these insights could be invaluable for understanding infection patterns, identifying high-risk populations, and designing targeted interventions [35]. For instance, AI-generated reports might reveal geographic areas with high rates of undiagnosed BBV infections, informing outreach and resource allocation strategies. These data-driven approaches **could** allow health authorities to refine their response to BBV epidemics in real-time.

Table 3 highlights AI's potential in data analysis and decision-making. Its capacity to clean data, detect anomalies, and forecast trends could enable more precise interventions and informed public health strategies.

Table 3
AI in Data Analysis and Decision Support.

AI Capability	Detailed Functionality	Impact on BBV Testing Programs
Data Cleaning and Validation [35]	Ensures data accuracy by correcting inconsistencies and filling gaps.	Could improve reliability of insights and clinical decisions.
Trend Analysis	Identifies shifts in BBV testing outcomes over time.	May inform strategic adjustments to protocols and resource planning.
Outcome Prediction	Predicts patient outcomes to guide interventions.	Could enable proactive, tailored care strategies.
Public Health Reporting	Creates detailed, actionable reports on prevalence and risk factors.	May enhance public health policies and resource distribution.
Anomaly Detection	Flags unexpected patterns in data for further review.	Could prevent overlooked outbreaks or unusual trends.

4.4. Enhancing patient engagement

Effective communication with patients is essential for the success of BBV opt-out testing programmes. Natural Language Processing (NLP), a subset of AI, has the potential to improve patient interactions. NLP tools could generate tailored messages that explain the testing process in clear, simple language, address common concerns, and reduce opt-out rates. This personalised approach may foster patient trust and cooperation, crucial for widespread programme acceptance.

However, BBV-specific evidence for these applications remains limited. AI-driven chatbots and mobile applications are being deployed in other healthcare contexts to enhance patient engagement before and after testing. These tools could potentially provide pre-test counselling, answer frequently asked questions, and guide patients through consent processes. Following testing, chatbots might deliver result notifications, offer initial advice, and connect patients to healthcare providers for further counselling or treatment. This digital-first approach could improve accessibility, particularly for patients facing barriers to face-to-face communication or follow-up care [36].

Patient engagement tools, as discussed in Table 4, could potentially use chatbots, personalised messaging, and pre-test counselling modules to reduce hesitancy and improve understanding of the testing process, though empirical evidence in BBV contexts remains limited.

Table 2
Workflow Enhancements Using AI.

AI Feature	Detailed Functionality	Benefits in Eds
Automated Test Ordering [34]	AI systems generate test orders based on eligibility criteria, reducing manual input.	Could free up staff to focus on direct patient care by reducing administrative tasks.
Real-Time Alerts	Alerts clinicians when high-risk patients are flagged, ensuring immediate action.	May minimise delays in initiating testing, improving patient outcomes.
Dynamic Scheduling	Adjusts staffing and resource allocation in response to patient inflow trends.	Could improve efficiency and reduces wait times during peak hours.
Task Prioritization	Sorts tasks by urgency, ensuring critical cases are addressed first.	May streamline workflows and enhances overall efficiency.
Integrated Reporting	Automatically generates and consolidates data for clinical and public health use.	Could support data-driven decision-making and public health strategies.

Table 4
Enhancing Patient Engagement with AI.

AI Tool	Enhanced Functionality	Advantages for Patients and EDs
Chatbots for Patient Communication	Engages patients with conversational AI, providing information and reassurance.	Could improve understanding and acceptance of testing processes.
Personalized Messaging [36]	Delivers customized messages addressing individual concerns and misinformation.	May build trust and fosters personalized patient care.
Pre-Test Counseling Modules	Provides interactive education on testing benefits and procedures.	Could reduce stigma and hesitation, encouraging participation.
Mobile App Integration	Offers access to educational resources, results, and reminders via apps.	May keep patients informed and engaged through accessible platforms.
Feedback Collection Tools	Collects insights to refine engagement strategies.	Could help EDs improve service delivery and patient satisfaction.

4.5. Follow-Up and continuity of care

One of the potential contributions of AI to BBV testing is in follow-up care. AI-powered systems could automate reminders for patients with positive test results, ensuring they are promptly contacted and linked to appropriate care providers. This may reduce the risk of losing individuals to follow-up, a common issue in busy ED settings. Additionally, AI tools could track patient engagement with follow-up services, providing insights into adherence rates and identifying gaps in care.

The practical realities of integrating primary care data present significant challenges not adequately addressed in current literature. Data governance hurdles, federated versus centralised storage architectures, and approval processes for data sharing between ED and primary care systems remain substantial barriers. Real-world examples of successful linkage implementation are scarce, particularly in BBV-specific contexts.

Predictive analytics may further enhance follow-up care by identifying barriers preventing patients from accessing treatment [37]. For example, AI models could analyse social determinants of health, such as housing instability or transportation challenges, to predict which patients are at risk of discontinuing care. This information may allow healthcare teams to implement targeted interventions, such as providing transportation vouchers or linking patients to community resources. By potentially addressing these barriers proactively, AI could support better health outcomes and reduce the public health burden of untreated BBV infections.

Table 5 outlines how continuity of care could potentially be enhanced through AI-driven follow-up notifications, care coordination platforms, and predictive adherence models, ensuring timely interventions and better long-term outcomes for BBV-positive patients.

Table 5
Follow-Up and Continuity of Care.

AI Function	Detailed Functionality	Impact on Patient Outcomes
Automated Follow-Up Notifications [37].	Sends reminders for appointments or treatments.	Could ensure timely follow-up, reducing delays in care.
Care Coordination Platforms	Links EDs with primary care and specialists for seamless transitions.	May enhance continuity of care and reduces fragmentation.
Predictive Adherence Models	Identifies patients at risk of non-adherence to follow-ups.	Could direct interventions to support adherence among high-risk groups.
Risk-Based Escalation	Prioritizes urgent cases for immediate attention.	May reduce morbidity by ensuring timely intervention.
Linkage to Care Systems	Connects patients to specialists and community resources.	Could facilitate comprehensive treatment and recovery.

5. Ethical considerations and challenges

The integration of Artificial Intelligence (AI) into blood-borne virus (BBV) opt-out testing in emergency departments (EDs) presents potential benefits alongside significant ethical considerations and practical challenges [38]. Addressing these issues is essential to ensure the responsible and equitable use of AI technologies, particularly in sensitive healthcare contexts. Key areas of concern include data privacy and security, biases in AI algorithms, challenges of integration and scalability, and the preservation of patient autonomy. BBV-specific ethical considerations require particular attention given the sensitive nature of infectious disease status and associated stigma.

5.1. Data privacy and security

AI systems in healthcare, especially those handling sensitive health data like BBV test results, must adhere to stringent data privacy and security standards. These systems process vast amounts of personal and medical information, making them potential targets for breaches or misuse. Robust encryption protocols, secure data storage systems, and strict access controls are critical to safeguarding patient information. Additionally, compliance with legal frameworks, such as the General Data Protection Regulation (GDPR) in Europe or similar regulations in other jurisdictions, is necessary to protect patient rights.

Privacy risks in handling infectious disease status present unique challenges beyond general healthcare data protection. The disclosure of BBV status can result in significant discrimination, social stigma, and personal harm. Data sharing with public health bodies raises additional concerns about patient confidentiality and the potential for stigmatisation of affected communities.

Ethical data use is equally vital, particularly in EDs that serve diverse populations [39]. Misuse or mishandling of data could exacerbate mistrust in healthcare systems, especially among marginalised groups. Transparency in collecting, processing, and using data is essential to maintain public trust and ensure patients know their rights and protections. Establishing ethical oversight committees to monitor AI implementations in BBV testing can provide an additional layer of accountability and safeguard against unethical practices.

5.2. Bias in AI algorithms

Bias in AI algorithms poses a significant ethical concern when applying these technologies to BBV testing. AI systems are only as reliable as the data used to train them, and training datasets often reflect existing disparities in healthcare access and outcomes. For instance, if algorithms are trained predominantly on data from specific demographics, they may fail to accurately predict outcomes or recommend testing for underrepresented groups. This can lead to inequities in testing and care, with particular populations being systematically overlooked or underserved.

In the context of BBV testing, algorithmic bias could disproportionately affect high-risk groups such as injection drug users, sex workers, homeless populations, and certain ethnic minorities. These groups may already face barriers to healthcare access, and biased AI systems could exacerbate these disparities by failing to appropriately identify them for testing or follow-up care.

Mitigating bias requires a proactive approach to dataset development, ensuring that data is representative of the diverse populations served by EDs [40]. Regular audits and evaluations of AI models should be conducted to identify and correct biases. Collaboration between technologists, clinicians, and public health experts can also help design algorithms that prioritise equity and inclusivity in BBV testing programmes.

5.3. Integration and scalability

Integrating AI systems into existing ED workflows and electronic health record (EHR) platforms presents technical and logistical challenges. These systems must be seamlessly incorporated into complex, fast-paced environments without disrupting standard operations. This requires significant investment in infrastructure, staff training, and system customisation to meet the specific needs of each ED. Additionally, ensuring compatibility between AI systems and existing technologies can be resource-intensive and time-consuming.

Scalability is another major hurdle, particularly in under-resourced settings where there is limited access to advanced technology and skilled personnel. Expanding AI-driven BBV testing programmes to such environments often requires innovative, cost-effective solutions tailored to the available infrastructure [41]. Partnerships with public health organisations, technology providers, and governments can help to address resource gaps and support broader implementation efforts.

5.4. Patient autonomy and consent

Respecting patient autonomy is fundamental in healthcare, and AI-driven BBV testing programmes must be designed to uphold this principle. Automated processes, while efficient, can inadvertently obscure patients' ability to make informed decisions about their care. It is essential that opt-out options are prominently communicated and that patients fully understand their rights to decline testing.

Consent strategies in BBV testing contexts require careful consideration. Following NIHR patient and public involvement guidelines, consent processes should be culturally sensitive and accessible to diverse populations. This includes providing information in multiple languages, ensuring understanding among patients with varying health literacy levels, and addressing specific concerns related to BBV stigma.

Transparency in the testing process, including how AI systems are used to identify and manage cases, is critical to maintaining trust and

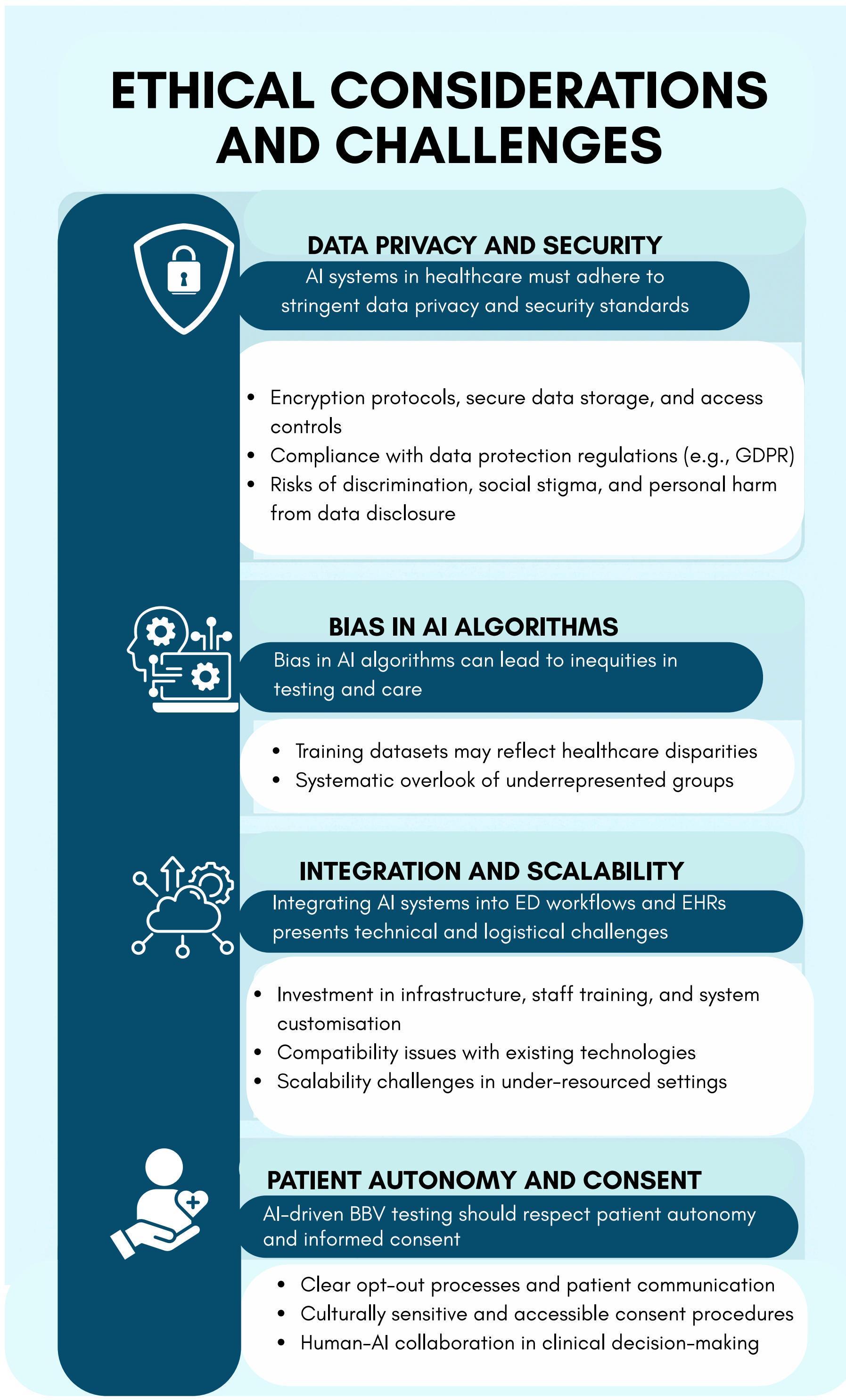

Fig. 3. Key Ethical and Practical Challenges in Implementing AI-Driven BBV Opt-Out Testing in Emergency Departments. The four main challenges data privacy and security, algorithmic bias, integration and scalability, and patient autonomy must be addressed to ensure responsible, equitable, and effective use of AI in BBV testing.

ensuring informed patient consent [42]. Moreover, AI systems must be designed to complement, rather than replace, human decision-making. While automation can streamline workflows, final decisions about patient care should involve clinicians who can consider contextual factors beyond what AI systems can analyse. This human-AI collaboration ensures that patient autonomy and individual circumstances remain at the forefront of healthcare delivery.

The main ethical and practical challenges associated with AI-driven BBV opt-out testing are summarised in Fig. 3, highlighting the importance of privacy, fairness, seamless integration, and respect for patient autonomy, with particular emphasis on BBV-specific considerations including infectious disease stigma and vulnerable population protection.

6. Implementation framework

To guide the translation of AI concepts into operational BBV testing programmes, a structured implementation framework is essential. We recommend adopting the Consolidated Framework for Implementation Research (CFIR) approach, which provides a comprehensive structure for understanding and addressing implementation challenges.

6.1. CFIR-based implementation strategy

The CFIR framework identifies five key domains that must be addressed for successful AI implementation in BBV opt-out testing. Intervention characteristics require AI systems to be designed with evidence-based features, adaptability to local contexts, and clear advantages over existing methods. For BBV testing specifically, this includes demonstrating improved accuracy in patient identification and workflow efficiency compared to traditional approaches. The outer setting encompasses external factors including regulatory requirements, funding mechanisms, and public health policies that must support AI implementation. Collaboration with public health authorities and alignment with national BBV elimination strategies is crucial for ensuring sustainable adoption.

Inner setting considerations focus on organisational factors within EDs, including leadership support, resource availability, and existing culture that must be conducive to technology adoption. This requires securing buy-in from clinical staff and administration whilst addressing potential resistance to change. Individual characteristics of healthcare providers, including their knowledge, skills, and attitudes towards AI technology, significantly influence implementation success. Comprehensive training programmes and change management strategies are essential to ensure effective adoption. Finally, the implementation process requires systematic planning, execution, and evaluation phases to be carefully managed, with meaningful stakeholder engagement maintained throughout the entire process.

6.2. NASSS framework considerations

Additionally, the Non-adoption, Abandonment, Scale-up, Spread, Sustainability (NASSS) framework provides valuable insights for ensuring long-term success of AI implementations in BBV testing programmes. Key considerations include understanding technology complexity and maturity levels, as immature or overly complex technologies may face adoption challenges in busy ED environments. The value proposition for different stakeholder groups must be clearly articulated, demonstrating benefits for patients, clinicians, administrators, and public health authorities. Organisational readiness and capacity for change varies significantly across healthcare settings, requiring tailored approaches that consider existing infrastructure, staff capabilities, and institutional culture. Wider system integration requirements must be carefully planned, ensuring that AI systems can effectively communicate with existing EHR platforms, laboratory systems, and public health databases. Finally, adaptation and co-evolution over time must be anticipated, with mechanisms in place for continuous improvement and system refinement based on real-world performance and changing healthcare needs. As shown in Fig. 4, aligning CFIR core domains with the NASSS lens provides a structured approach to understanding both the internal and external factors influencing AI adoption in emergency departments.

7. Future Directions and recommendations

The successful integration of Artificial Intelligence (AI) into bloodborne virus (BBV) opt-out testing programmes in emergency departments (EDs) requires a comprehensive approach that addresses research gaps, policy development, implementation challenges, and stakeholder engagement. The following recommendations outline priority areas for advancing this field whilst acknowledging current limitations in BBV-specific evidence.

7.1. Research and development priorities

Ongoing research is critical to bridge the gap between theoretical potential and empirical evidence for AI applications in BBV opt-out testing. BBV-specific validation studies represent the most urgent research priority, as rigorous evaluation of AI applications specifically in BBV contexts is needed to establish empirical evidence. Studies should focus on measurable outcomes such as improved detection rates, reduced opt-out rates, enhanced follow-up compliance, and patient satisfaction. These evaluations will provide evidence-based insights into the impact of AI technologies, enabling continuous refinement of algorithms and strategies that can demonstrate real-world effectiveness.

Comparative effectiveness research, including head-to-head comparisons between AI-enhanced and traditional BBV testing approaches, is essential to demonstrate clinical and operational benefits. Such studies should employ robust methodologies including randomised controlled trials where feasible, providing the high-quality evidence needed to support policy decisions and clinical adoption. Addressing algorithmic bias must be given priority through developing and validating AI models using diverse and representative datasets that include underserved populations at higher risk for BBV infections. Research should specifically examine algorithm performance across different demographic groups, socioeconomic strata, and risk categories to ensure equitable outcomes.

Integration studies exploring the combination of AI with emerging technologies, such as point-of-care testing devices, wearable technology, and telehealth platforms, could expand the reach and efficiency of BBV testing programmes. Pilot studies conducted in various healthcare settings, including resource-constrained environments, can provide valuable data to inform broader implementation efforts and ensure that solutions are adaptable to diverse clinical contexts.

7.2. Policy and governance framework

Developing comprehensive guidelines for the ethical use of AI in BBV testing is essential to safeguard patient rights and maintain public trust. Regulatory framework development should emphasise robust data privacy and security measures, protecting sensitive health information against misuse or breaches. Regulatory frameworks must address accountability, requiring transparent reporting of AI system performance and decision-making processes whilst ensuring compliance with existing healthcare regulations and emerging AI governance standards.

Interdisciplinary governance approaches require collaboration among technologists, clinicians, public health experts, policymakers, and patient advocates for successful governance of AI systems. Governance structures should reflect the complexities of healthcare delivery whilst aligning with public health goals, ensuring that diverse perspectives inform policy development. International standardisation efforts can support the development of best practices, particularly for cross-

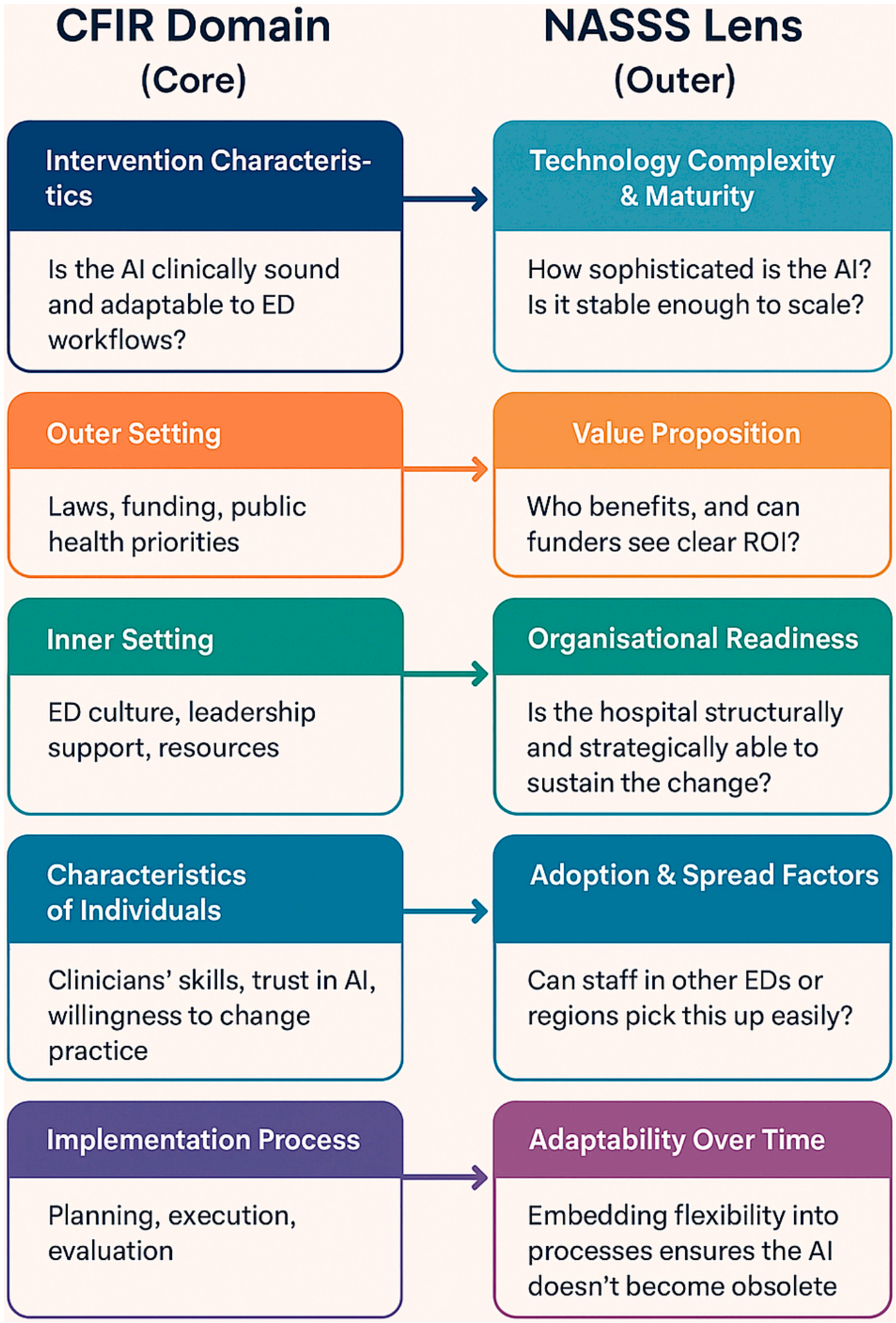

Fig. 4. Conceptual alignment between the Consolidated Framework for Implementation Research (CFIR) core domains and the Non-adoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) lens. The framework illustrates how internal implementation factors (CFIR) intersect with external adoption considerations (NASSS) in the context of deploying artificial intelligence (AI) in emergency departments (EDs). Each pairing highlights a key connection—such as linking clinical soundness with technological maturity or aligning external drivers with a strong value proposition—emphasizing the dual focus required for effective adoption, scale-up, and sustainability.

border health initiatives and global BBV elimination efforts, facilitating knowledge sharing and coordinated responses.

Ethical oversight mechanisms must be established through independent ethics committees specifically focused on AI in healthcare, with particular expertise in infectious disease contexts and vulnerable population protection. These committees should provide ongoing monitoring of AI implementations, ensuring that ethical principles are maintained throughout the lifecycle of AI systems and that emerging ethical challenges are promptly addressed.

7.3. *Training and implementation strategy*

For AI-driven BBV testing programmes to be effective, comprehensive training and implementation strategies are required that address the diverse needs of healthcare providers and organisations. Healthcare provider education must ensure that ED staff are adequately trained in using AI tools, interpreting AI-generated insights, integrating these tools into existing workflows, and addressing ethical considerations. Training programmes should emphasise the limitations and potential biases of AI systems whilst maintaining clinical judgement and patient-centred care. This education should be ongoing, recognising that AI technologies continue to evolve and that staff competencies must be maintained and updated accordingly.

Scalable implementation models require the development of flexible AI models that can be adapted to diverse healthcare settings for widespread adoption. These models should accommodate varying resource levels, from well-equipped urban centres to resource-limited rural clinics, ensuring that technological solutions do not exacerbate existing healthcare disparities. Cost-effectiveness analysis represents a critical component of implementation planning, with comprehensive economic evaluations comparing AI-enhanced testing programmes with traditional approaches needed to inform funding decisions and policy development.

Change management strategies must employ systematic approaches to managing organisational change, addressing staff resistance, and ensuring sustainable adoption of AI technologies. These strategies should recognise the complexity of healthcare environments and the importance of engaging stakeholders throughout the implementation process to build support and address concerns proactively.

7.4. Stakeholder engagement and public involvement

Engaging patients, communities, and healthcare providers in the design and implementation of AI systems is vital to ensure these technologies meet user needs and address concerns effectively. Patient and public involvement, following NIHR guidelines, requires meaningful engagement with patients and communities to guide the development of user-friendly interfaces and culturally sensitive communication strategies. This engagement should specifically include populations at higher risk for BBV infections who may face additional barriers to healthcare access, ensuring that technological solutions address rather than compound existing inequities.

Community engagement efforts focused on raising awareness about the benefits of BBV opt-out testing whilst addressing stigma and encouraging participation require sustained commitment and culturally appropriate approaches. AI-driven communication tools should be co-designed with target communities to ensure cultural appropriateness and effectiveness, recognising that different populations may have varying concerns and preferences regarding healthcare technology.

Healthcare provider engagement involves including frontline ED staff in the design and testing of AI systems to ensure practical relevance and increase the likelihood of successful adoption. This engagement should recognise the expertise of clinical staff whilst addressing their concerns about workflow integration and patient safety. Continuous feedback mechanisms must be established for ongoing stakeholder feedback to enable iterative improvement of AI applications and implementation strategies, ensuring that systems evolve to meet changing needs and address emerging challenges.

7.5. Technology development priorities

Technical advancement should focus on several key areas to ensure successful integration of AI systems into BBV testing programmes. Interoperability standards require developing AI systems that can seamlessly integrate with existing EHR platforms and healthcare information systems, recognising that healthcare environments often involve multiple software platforms that must communicate effectively. This technical compatibility is essential for ensuring that AI tools enhance rather than complicate existing workflows.

Real-world performance monitoring involves implementing systems for continuous monitoring of AI performance in live clinical environments, with mechanisms for rapid adjustment and improvement when performance issues are identified. This ongoing monitoring is crucial for maintaining system accuracy and reliability whilst identifying opportunities for enhancement. Privacy-preserving technologies represent another critical development priority, advancing techniques such as federated learning and differential privacy to enable AI development whilst protecting patient confidentiality and meeting stringent healthcare data protection requirements.

User interface design must focus on creating intuitive, efficient interfaces that enhance rather than complicate clinical workflows, recognising that successful adoption depends largely on the ease of use and practical utility of AI tools for busy healthcare providers. These interfaces should be designed with input from end users to ensure they meet real-world needs and support rather than hinder clinical decision-making processes.

8. Conclusion

The integration of Artificial Intelligence (AI) into blood-borne virus (BBV) opt-out testing in emergency departments (EDs) represents a potential opportunity to enhance public health outcomes. AI's capacity to streamline workflows, optimise resource allocation, and provide data-driven insights may significantly address the operational inefficiencies that often hinder the implementation of these testing programmes. Additionally, AI-powered tools could potentially improve patient engagement through personalised communication and automated follow-up systems, ensuring a seamless and patient-centred approach to care. By leveraging these capabilities, AI has the theoretical potential to enhance detection rates, facilitate early treatment, and ultimately reduce the burden of BBVs on both individuals and healthcare systems. However, this review reveals a significant gap between theoretical potential and empirical evidence specifically related to BBV testing in ED settings. While AI applications in broader healthcare contexts show promise, BBV-specific validation remains limited, highlighting the need for targeted research and evidence generation.

Despite its promise, the adoption of AI in BBV testing faces substantial challenges. Data privacy and security concerns remain critical, particularly given the sensitive nature of BBV-related information and the unique stigma associated with infectious disease status. Addressing algorithmic biases is equally essential to ensure that AI systems do not perpetuate existing healthcare inequities or disproportionately affect vulnerable populations at higher risk for BBV infections. Furthermore, the scalability of AI-driven solutions poses a significant hurdle, especially in under-resourced settings where access to advanced technologies and skilled personnel may be limited. Real-world implementation barriers including staff training requirements, system interoperability issues, cost implications, resistance from clinical personnel, and IT infrastructure limitations in public hospitals must be systematically addressed. Overcoming these challenges requires a coordinated approach that combines technological innovation with ethical oversight and strategic investment in infrastructure.

Moving forward, several critical research priorities must be addressed. First, BBV-specific validation studies are urgently needed to establish empirical evidence for AI applications in this context. Second, comprehensive implementation frameworks such as CFIR and NASSS should guide systematic deployment of AI technologies. Third, robust governance structures must be established to address the unique ethical considerations associated with BBV testing, including infectious disease stigma and vulnerable population protection.

Collaborative efforts between technologists, clinicians, policymakers, and community stakeholders are essential to ensure that AI systems are designed and deployed in alignment with ethical standards and public health goals. As the healthcare landscape evolves, integrating AI into BBV testing programmes must prioritise inclusivity, transparency, and patient autonomy. Empowering patients and communities through clear communication and engagement will foster trust and acceptance of these technologies. Meaningful patient and public involvement, following established guidelines, should guide technology development and implementation strategies.

At the same time, multidisciplinary collaboration will ensure that AI systems are tailored to meet the diverse needs of EDs and their patient populations whilst addressing real-world implementation challenges.

Overall, while AI presents promising theoretical applications for BBV opt-out testing programmes, the field requires substantial empirical validation, systematic implementation frameworks, and comprehensive stakeholder engagement to realise its potential. By addressing current evidence gaps and implementation challenges with rigour and foresight, AI could potentially contribute to more equitable, efficient, and impactful solutions that advance global efforts to eliminate blood-borne viruses. However, realistic expectations must be maintained regarding the current evidence base and the significant work required to translate theoretical possibilities into clinical reality.

CRediT authorship contribution statement

Adebayo Da'Costa: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Jennifer Teke:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Joseph E. Origbo:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Clarissa Madla:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Ayokunle Osonuga:** Writing – review & editing, Validation, Methodology, Investigation. **David B. Olawade:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Project Management.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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