Artificial Intelligence–Based Digital Interventions for HIV Prevention in Sexual and Gender Minority Populations Globally: A Systematic Review

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Abstract

Sexual and gender minority populations experience high HIV incidence, and digital interventions offer prevention opportunities. Artificial intelligence (AI) enables adaptive, personalized support, yet quantitative evidence in sexual and gender minority communities remains limited. This systematic review examined the effectiveness and implementation of AI-powered digital HIV prevention interventions. Five databases were searched from inception to June 2025 for randomized trials, quasi-experimental studies, and feasibility studies using adaptive AI features. Risk of bias was assessed with RoB 2, ROBINS-I, and NIH tools. Findings were synthesized narratively. From 380 records, seven studies (n = 1,729) met the inclusion criteria. Interventions included AI-driven chatbots, adherence monitoring systems, and a simulation game targeting preexposure prophylaxis adherence, HIV testing, and sexual risk reduction. Chatbots showed the consistent behavioral effects, particularly in increasing HIV self-testing and preexposure prophylaxis uptake. Across studies, feasibility, engagement, and usability were high. AI-based digital interventions show promise, but rigorous trials are needed to strengthen the evidence.

Key words: artificial intelligence, digital technology, HIV prevention, preexposure prophylaxis, sexual and gender minorities

HIV remains a critical global public health challenge, with an estimated 40.8 million people living with the virus in 2024 and approximately 1.3 million new infections annually (UNAIDS, 2025; World Health Organization, 2025). Despite a notable decline in new infections since 2010, global aims to reduce the number of new HIV infections annually to 370,000 by 2025 have not been met (UNAIDS, 2025). Sexual and gender minority (SGM) populations, including gay and bisexual men and transgender individuals, remain disproportionately affected. The global HIV prevalence is estimated at 7.6% among men who have sex with men (MSM) and 8.5% among transgender individuals, far exceeding the prevalence in the general population (UNAIDS, 2025). Addressing HIV disparities in these groups remains a public health priority.

Digital health interventions have emerged as scalable, cost-effective strategies to increase HIV prevention efforts globally. Existing tools, such as mobile apps, short message service (SMS) reminders, and web-based programs, have demonstrated benefits for HIV testing promotion, preexposure prophylaxis (PrEP) uptake, and adherence across diverse settings (Guide to Community Preventive Services, 2021; Lee et al., 2023). It is important that digital interventions have also been used to promote condom use, improve mental health outcomes, address substance use–related sexual risk, and support behavioral risk reduction (Gilbey et al., 2020; Meiksin et al., 2021). Systematic reviews indicate that digital tools can improve PrEP-related outcomes among MSM and that digital platforms can reduce PrEP-related stigma among MSM and transgender women by providing anonymous, judgment-free support (Du et al., 2025; Lee et al., 2023). However, most conventional digital HIV programs rely on static or rule-based content (e.g., fixed SMS reminders, prescheduled educational modules), limiting their ability to adapt dynamically to individuals' changing risk levels, motivations, or behavioral patterns (Brisson et al., 2025; Haines et al., 2024).

Artificial intelligence (AI) offers new opportunities to advance digital HIV prevention by enabling precision, personalization, and real-time adaptation at scale. In our review, AI-based interventions are defined as digital tools that use AI techniques, such as machine learning (systems that learn from data to improve performance; Marcus et al., 2020), natural language processing (NLP;

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technologies enabling computers to understand and generate human language; Feller et al., 2018), or predictive analytics (data-driven models that estimate future risk or behaviors; Molldrem et al., 2023) to deliver or tailor HIV prevention content. Key applications include machine learning algorithms that estimate HIV risk at the individual level using multiple behavioral and contextual factors, NLP-driven chatbots for real-time counseling, and recommender systems that personalize prevention messages addressing PrEP uptake, condom use, substance use–related risk, or reductions in high-risk sexual behaviors (Kundu et al., 2021; Salazar-Vizcaya et al., 2025; Xin et al., 2020). For example, algorithm-guided identification of peer leaders in online networks has achieved superior reductions in risky behaviors compared with traditional human-selected approaches (Young et al., 2020).

These AI-enabled mechanisms may be especially valuable for SGM populations, who face unique barriers to HIV prevention, such as stigma in health care settings, limited access to culturally competent services, and concerns about privacy and disclosure (Guzman Herrera et al., 2024; Joudeh et al., 2021). AI-driven digital platforms can deliver confidential, identity-affirming counseling, sustain engagement through interactive chatbots, and optimize PrEP or test reminders on the basis of real-time behavioral patterns (Bragazzi et al., 2023; Van Heerden et al., 2023). Early evidence suggests that AI-enabled tools are acceptable and feasible for SGM users, with improvements observed in PrEP knowledge, uptake, and adherence (Kamitani et al., 2024; Van Heerden et al., 2023).

From a nursing perspective, AI-enabled digital HIV prevention interventions have important implications. Nurses play a central role in HIV prevention, and AI-driven digital tools complement nurse-led care by enabling individualized risk assessment, delivering consistent culturally affirming counseling, and optimizing HIV testing or PrEP messaging (Threats et al., 2021; Zhang et al., 2024). Additionally, understanding AI-enabled interventions is vital for nursing education and research, equipping nurses to critically appraise digital health technologies, address ethical issues like privacy and bias, and contribute to designing and evaluating technology-supported HIV prevention strategies (El Arab et al., 2025; Mohammed et al., 2025).

Several recent reviews have explored AI and digital technologies in HIV prevention broadly. For example, Yuliana et al. (2025) highlighted pilot-stage AI applications, including risk detection and tailored educational chatbots; Babatunde et al. (2025) demonstrated the moderate to high accuracy of AI prediction tools for identifying HIV risk and optimizing PrEP eligibility but underscored the need for standardization. Van Heerden et al. (2023) emphasized the promise of AI chatbots while identifying key ethical and technical challenges, such as privacy and user trust. Despite these advances, no existing review has synthesized quantitative evidence on the effectiveness of AI-driven digital interventions specifically among SGM populations. This represents a critical gap, as the prevention needs, behavioral patterns, and structural barriers faced by SGM communities differ substantially from those of the general population.

To address this gap, our present systematic review synthesizes current quantitative evidence on the effectiveness, mechanisms, and implementation of AI-enabled digital interventions for HIV prevention among SGM. Rather than evaluating a single intervention, our review critically examines how existing AI-driven digital strategies have been studied, what outcomes they have achieved, and where evidence remains limited or preliminary. By mapping the evidence across AI modalities, delivery channels, and SGM subgroups, our review aims to inform future research, program design, and policy development to advance equitable and data-informed HIV prevention strategies.

Methods

Protocol and Registration

Our review followed the PRISMA 2020 guidelines (Page et al., 2021) and was preregistered in the PROSPERO (CRD420251147165).

Eligibility Criteria

Population. Studies were eligible if they included individuals identified as SGM, including but not limited to gay, bisexual, MSM, transgender and gender-diverse people, lesbian and bisexual women, and nonbinary individuals. Studies enrolling mixed populations were included if SGM-specific outcomes were reported separately or if SGM participants constituted at least 70% of the study sample.

Eligible participants were HIV uninfected or of unknown HIV status and considered at risk for HIV acquisition. Studies that enrolled only SGM individuals living with HIV or focused exclusively on HIV treatment outcomes (i.e., antiretroviral therapy adherence or viral suppression) were excluded. No restrictions were applied to age, setting, or country.

Interventions. AI-based digital interventions were operationally defined as systems that incorporated computational intelligence capable of learning from data, generating predictions, adapting outputs, or autonomously processing user input (Haenlein & Kaplan, 2019). Interventions qualified as AI-based if they explicitly identified AI (e.g., machine learning, deep learning, algorithmic personalization, AI-driven chatbot) or if they incorporated AI functionalities even without explicit labeling. These functionalities included machine learning for prediction or personalized recommendations, natural language processing for intent recognition or conversational generation, reinforcement learning for optimizing message timing or content, and computer vision for automated detection relevant to HIV prevention.

To ensure conceptual clarity during screening, we distinguished AI-driven adaptivity from rule-based automation. Interventions were classified as AI-based only when feedback, recommendations, or decisions were dynamically adjusted through statistical or computational models, rather than predetermined scripts or static branching logic. Early interventions (such as simulation-based systems) were included only when their core engines demonstrated adaptive computational behavior that met these predefined criteria, rather than simple rule-based gamification.

Interventions were excluded when they relied solely on fixed rules or scripts, delivered only static reminders or educational content, or focused exclusively on HIV treatment rather than prevention.

Comparators. All types of comparison conditions were eligible. These included no intervention, waitlist controls, usual care, informational or educational materials, standard (non–AI-based) digital interventions, or alternative behavioral or digital interventions.

Outcomes. Primary outcomes (effectiveness) included HIV testing uptake, defined as the proportion of participants who completed HIV testing during or after the intervention; PrEP outcomes, including initiation, adherence, and persistence with PrEP regimens; and risk reduction behaviors such as changes in condomless sex, number of sexual partners, or incidence of HIV or sexually transmitted infections.

Secondary outcomes (mechanisms and mediators) included cognitive and motivational mediators, such as HIV-related knowledge, risk perception, self-efficacy, and prevention attitudes, as well as AI-specific mechanisms including predictive accuracy (such as area under the receiver operating characteristic curve, sensitivity, and specificity), degree of personalization or adaptivity, and AI-driven user engagement (such as chatbot responsiveness and adaptive message timing).

Implementation and acceptability outcomes included in our review were engagement metrics (retention, interaction frequency), acceptability and usability (satisfaction, perceived helpfulness, trust, intention to continue), and feasibility and reach (recruitment success, adherence to protocols, scalability). All outcomes were extracted at the time points reported in each study, without a prespecified uniform follow-up period.

Study design. Given the emerging and rapidly evolving nature of AI-based HIV prevention tools, we adopted a tiered evidence framework to capture both effectiveness data and early-stage implementation insights. Studies were therefore categorized as follows:

Tier 1 (primary evidence): Randomized controlled trials (individual or cluster). These designs provide the strongest causal inferences about intervention effects.

Tier 2 (secondary evidence): Nonrandomized comparative designs, including quasi-experimental studies, controlled before–after studies, and interrupted time-series analyses with a comparator. These studies offer suggestive evidence of effectiveness when RCTs are not feasible but remain susceptible to confounding.

Tier 3 (exploratory evidence): Single-group pre–post studies, pilot trials without a control arm, and quantitative or mixed methods evaluations focusing on feasibility, acceptability, or engagement. These studies were included because AI-enabled interventions often require iterative development, real-world testing, and user-experience optimization before formal trial evaluation (McAlister et al., 2025). They therefore inform implementation potential and technology readiness, which align with our objective of characterizing how AI tools function in practice. However, no conclusions regarding intervention effectiveness were drawn from Tier 3 evidence; such studies were interpreted only in terms of feasibility, acceptability, and user engagement.

Purely qualitative studies, cross-sectional surveys without an intervention, protocols without results, case reports/series, and editorials/commentaries were excluded.

Language and time frame. Studies published in English from database inception to June 2025 were eligible. Although AI-based interventions are relatively recent, searches were conducted from database inception to ensure comprehensive identification of early computational or algorithm-driven digital interventions relevant to HIV prevention.

Search Strategy

Comprehensive searches were conducted through PubMed, Scopus, Embase, CINAHL, and ProQuest, using combining Terms: (population) AND (intervention) AND (outcomes) AND (delivery methods) covering SGM populations, AI-based intervention, HIV prevention–related outcomes, and digital delivery adapted per database. No study design was filtered at the database level to maximize sensitivity; design classification occurred at screening. Citation (snowballing), reference list searching, and relevant systematic reviews were screened for additional studies. The detailed strategies are presented in Appendix 1, http://links.lww.com/JNC/A108.

Study Selection Process

After deduplication in EndNote, two reviewers independently screened titles/abstracts and full texts. The exclusion for ineligible records was documented (Appendix 2, http://links.lww.com/JNC/A109). Discrepancies were resolved by consensus or third reviewer adjudication. The selection process is illustrated in a PRISMA flow diagram (Figure 1).

Risk of Bias Assessment

Two reviewers independently evaluated the methodological quality of all included studies. For the two randomized controlled trials, we applied the Cochrane Risk of Bias 2 (RoB 2) tool, following the guidance of Sterne et al. (2019). The quasi-experimental implementation study was assessed through the ROBINS-I (Sterne et al., 2016), and the four single-group feasibility or usability studies were appraised through the NIH quality assessment tool for before-after (pre–post) studies with no control group (NHLBI, 2013). Discrepancies were resolved through discussion or consultation with a third reviewer. Each study was assigned an overall risk-of-bias rating (low,

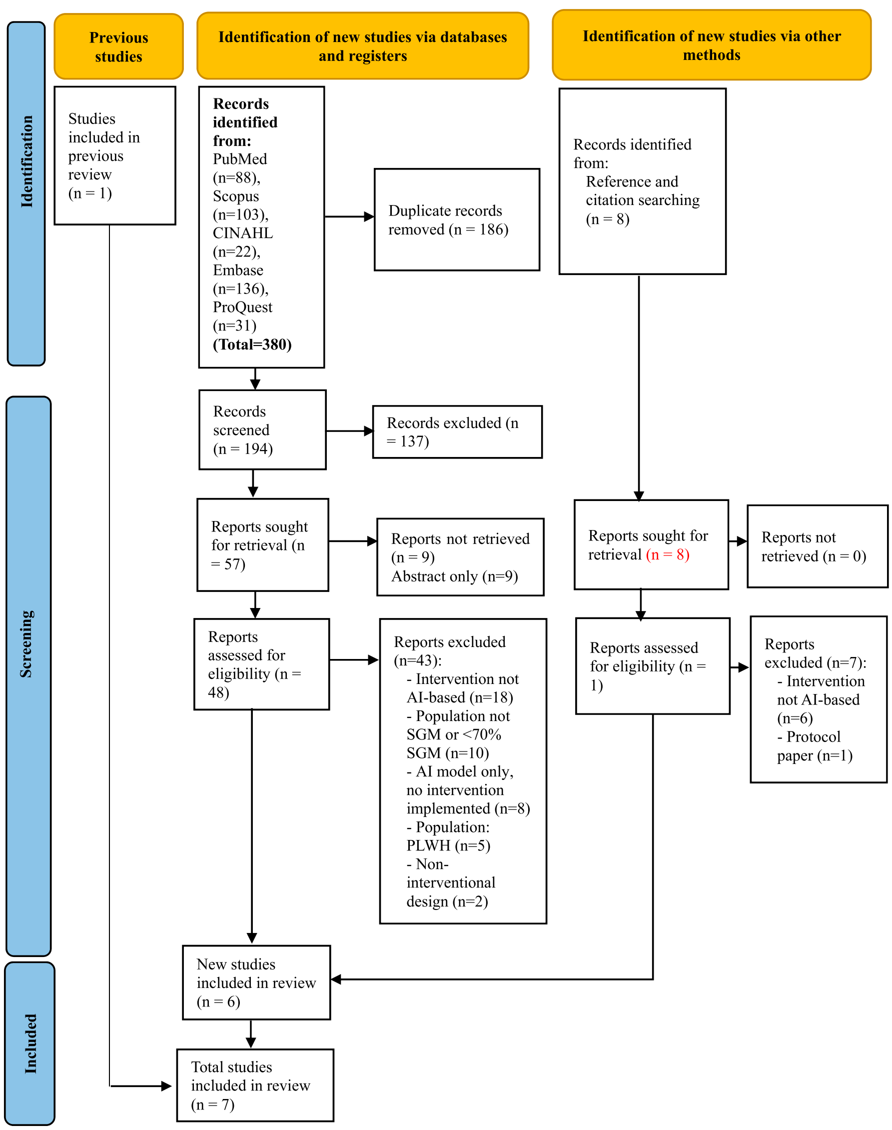

Figure 1. The PRISMA Flow Chart. *Note.* PLWH = people living with HIV; SGM = sexual and gender minority.

some concerns, or high). A summary table was generated to visually present the risk-of-bias judgments across studies.

Data Extraction

Data extraction was conducted independently by two reviewers using a piloted extraction form. The extracted data were cross-checked, and discrepancies were resolved through discussion and consultation with a third reviewer. The authors of the primary studies were contacted when clarification or additional information was needed. The following information was extracted from each included study:

Study characteristics: author, publication year, study design, country, setting, recruitment method, sample size, population subgroup, and mean or median age.

Intervention characteristics: AI modality (such as chatbots and recommender systems), application focus (such as PrEP adherence and HIV testing), delivery channel (such as apps and webs), intensity or duration, and the presence of a comparator.

Outcome measures: primary behavioral outcomes (such as HIV testing uptake, PrEP adherence), secondary or mechanistic outcomes (such as AI accuracy), and implementation outcomes (such as engagement, acceptability, and feasibility). For each outcome, data on the measurement method, follow-up timing, and statistical significance were extracted.

The extracted data were synthesized and summarized into structured evidence tables describing the study characteristics, intervention features, and main findings across the outcome domain.

Data Synthesis

Because of the limited number of eligible studies and variability in study designs, AI modalities, and outcome measures, a quantitative meta-analysis was not feasible. Instead, findings were synthesized narratively following the guidance of the Cochrane Handbook for Systematic Reviews of Interventions and the synthesis without meta-analysis reporting framework (Campbell et al., 2020). The evidence was organized and interpreted according to three domains. Effectiveness outcomes (e.g., PrEP adherence and HIV testing uptake) were compared qualitatively across AI modalities and delivery formats. Mechanistic outcomes (e.g., AI accuracy) were summarized to illustrate how AI-specific features may influence behavioral or engagement outcomes. The implementation outcomes (i.e., engagement, acceptability, and feasibility) were synthesized across all study designs to identify patterns in adoption, scalability, and population reach.

To reflect differences in methodological strength, studies were classified into evidence tiers: Tier 1 (randomized controlled trials), Tier 2 (quasi-experimental studies), and Tier 3 (single-group pre–post or feasibility studies). The evidence was integrated within and across tiers to highlight converging trends and variations in effectiveness. Heterogeneity across studies was described qualitatively in terms of design, intervention modality, population, and outcome measurement.

Results

Study Selection and Study Characteristics

The initial search identified 380 records, seven of which met the inclusion criteria after full-text review (Figure 1). Excluded studies mainly lacked AI-based components, focused on non-SGM populations, targeted people living with HIV exclusively, or were noninterventional. A full exclusion list is provided in Appendix 2, http://links.lww.com/JNC/A109.

Seven studies ($n = 1,729$ participants) were conducted between 2013 and 2025 across the United States ($n = 4$), Malaysia ($n = 2$), and Brazil ($n = 1$). Most studies targeted MSM (6/7), and two included transgender women. The participants were typically ages 21–28 years, and recruitment was primarily digital, leveraging platforms such as Grindr, Facebook, WhatsApp, and TikTok (Table 1).

Overall, the methodological quality was acceptable but heterogeneous across the study designs (Table 2). The two RCTs were rated as having a low to moderate risk of bias, with minor concerns related to intervention fidelity and outcome measurement. The quasi-experimental study revealed a serious risk primarily from uncontrolled confounding and participant selection bias. The four pre–post studies were generally of fair to good quality, although recurrent limitations included small sample sizes, lack of blinding, and incomplete follow-up.

Across all designs, biases were most evident in internal validity domains, particularly confounding, missing outcome data, and the absence of independent outcome verification. By contrast, reporting quality and intervention descriptions were generally adequate, supporting interpretability. Although none of the studies had high or critical risk across all domains, the predominance of single-arm feasibility designs and short follow-up periods limits confidence in behavioral outcome effects. However, implementation and acceptability findings appear more robust, as these outcomes were consistently measured with standardized tools.

Table 1. Study and Participant Characteristics Among the Included Studies

First author, year	Tier/Study Design	Country	Setting (Location/ Study Context)	Recruitment Method	Population (SGM Subgroup)	Sample (*n*, per Group)	Age (*M* ± *SD*/ Range)
Buchbinder et al. (2023)	Tier 1—RCT	United States	Community PrEP clinics (Atlanta and San Francisco)	Clinic-based recruitment	MSM	*N* = 100 (intervention = 66, control = 34)	Mean = 26 years
Cheah et al. (2024)	Tier 3—mixed methods feasibility	Malaysia	Remote HIV testing via Zoom	Social apps (Grindr, Hornet, Blued, WhatsApp)	MSM	*N* = 14 (single group)	Mean = 25.6 ± 4.2 years
Christensen et al. (2013)	Tier 1—RCT	United States	Web-based HIV-prevention game	Online banners on MSM sites	MSM	*N* = 921 (intervention = 437, control = 484)	Mean = 21.3 ± ~1.8 years
Dos Santos et al. (2024)	Tier 3—usability subanalysis of RCT	United States	mLab mobile platform	Facebook, Instagram, Grindr ads + community referrals	MSM, TGW	*N* = 210 (single group)	Mean = 24.3 ± 3.2 years
Liu et al. (2021)	Tier 3—single group pre–post pilot	United States	Community-based PrEP clinics and research sites (San Francisco and Atlanta)	PrEP clinic cohorts	MSM	*N* = 20 (single group)	Median = 28 years (range 20–32)
Massa et al. (2023)	Tier 2—quasi-experimental implementation	Brazil	Facebook Messenger chatbot linked to PrEP clinics	Social media and peer outreach	MSM, TGW	*N* = 130 (single group)	Age range: 15-19 years
Ni et al. (2025)	Tier 3—national observational usability	Malaysia	Web-based chatbot (MYHIV365)	Community outreach and social apps (WhatsApp, Twitter, Telegram, Facebook, TikTok, Grindr, Instagram)	MSM	*N* = 334 (single group)	≥18 years

Note. *n* = 7. RCT = randomized controlled trial; TGW = transgender women.

Intervention Characteristics and Comparators

Table 3 summarizes the intervention features and comparators. Four interventions used AI-driven chatbots, two used adherence-monitoring or recommender systems, and one employed an AI-enabled simulation game. Three focused on PrEP adherence, three on HIV testing, and one on sexual risk reduction. Mobile applications and chatbots were the predominant delivery formats, providing adaptive feedback, conversational interaction, and personalized reminders.

Intervention intensity ranged from single 30- to 45-minute sessions to sustained daily engagement more than 8–24 weeks. Comparators were limited to two studies: a standard-of-care control (Buchbinder et al., 2023) and a wait-list control (Christensen et al., 2013).

Effects of AI-Based Interventions

Table 4 summarizes the main findings of the included studies. AI-based interventions demonstrated promising effects on key HIV prevention behaviors, particularly in

Table 2. Assessment of the Quality of the Included Studies

Study	Tool	Overall Risk/Quality	Key Sources of Bias
Buchbinder et al. (2023)	RoB 2	Low	Some concern for deviations from intended interventions
Christensen et al. (2013)	RoB 2	Some concern	Deviations from intended interventions, missing outcome data, and outcome measurement
Massa et al. (2023)	ROBINS-I	Serious	Confounding as the main source; additional concerns for participant selection and selective reporting
Cheah et al. (2024)	NIH pre–post	Fair	Small sample size, incomplete follow-up, lack of assessor blinding, and potential uncontrolled confounding
Dos Santos et al. (2024)	NIH pre–post	Good	Generally, strong reporting; minor issues with enrollment clarity and lack of multiple-measure adjustments
Liu et al. (2021)	NIH pre–post	Good	Unclear enrollment of all eligible participants, small sample size, and absence of assessor blinding
Ni et al. (2025)	NIH pre–post	Fair	Unclear enrollment, lack of assessor blinding, limited control for confounding, and absence of multiple measures

Note. $n = 7$. RoB 2 = revised Cochrane risk of bias tool; ROBINS-I = risk of bias in nonrandomized studies of interventions; NIH = NIH quality assessment tool for before–after studies.

promoting HIV testing and PrEP engagement. Chatbot-based interventions showed the most robust behavioral outcomes: for example, HIV self-testing orders increased to 66.2% among MSM users (Ni et al., 2025), and chatbot interactions accounted for 17.4% of new PrEP initiations in Brazil (Massa et al., 2023). Simulation-based AI, an interactive virtual environment that allows participants to practice sexual decision making and condom negotiation, also significantly reduced condomless sex, which was mediated by reductions in sexual shame (Christensen et al., 2013).

By contrast, AI-enabled adherence monitoring systems enhanced the accuracy and objectivity of adherence assessment (Buchbinder et al., 2023; Liu et al., 2021) but did not independently improve adherence behavior without additional behavioral or motivational support. Collectively, these findings indicate that although AI can effectively facilitate HIV prevention engagement, its behavioral impact may depend on complementary psychosocial components.

Mechanisms, Acceptability, and Implementation Outcomes

None of the included studies explicitly tested psychosocial mediators, such as knowledge, risk perception, or self-efficacy. However, several interventions reported AI-specific performance indicators that illuminate potential mechanisms of action. In Buchbinder et al. (2023), the directly observed therapy (DOT) Diary app showed a high level of concordance with FTC-TP and TFV-DP levels (91.0 and 85.3%, respectively), suggesting that this method of measuring adherence is substantially better than self-reported measures. Similarly, chatbot engagement metrics revealed sustained conversational interactivity (Ni et al., 2025), indicating user responsiveness to dynamic, adaptive communication.

Across all studies, AI-based interventions achieved high levels of engagement, acceptability, and feasibility among SGM participants. The reported System Usability Scale (SUS) scores ranged from 76 to 80 (Buchbinder et al., 2023; Cheah et al., 2024), and user satisfaction exceeded 90% in most trials (Liu et al., 2021; Massa et al., 2023; Ni et al., 2025). Engagement was greatest in interactive formats, such as video chatbots and simulation games, which elicited immediate and immersive participation (Cheah et al., 2024; Christensen et al., 2013). Mobile applications maintained long-term engagement but gradually declined over time (Buchbinder et al., 2023; Liu et al., 2021), reflecting a common

Table 3. Intervention and Comparator Characteristics Among the Included Studies

Author (Year)	AI Type	Application Focus	Delivery Channel	Duration or Intensity	Comparator
Buchbinder et al. (2023)	AI-enabled recommender/ adherence monitoring system	PrEP adherence support	Smartphone mobile app	Daily dosing verification for 24 wks	Standard of care
Cheah et al. (2024)	AI chatbot	HIV testing and PrEP promotion	Zoom video platform	Single 45-min interactive session	Single group (no comparator)
Christensen et al. (2013)	AI-driven simulation game	Reduction of sexual shame and condomless anal intercourse	Downloadable computer-based virtual environment	Single-session gameplay (~30 min)	Wait-list control
Dos Santos et al. (2024)	AI chatbot	HIV testing and linkage to care	mLab mobile app	On-demand access with 3-month testing reminders	Single group (usability evaluation)
Liu et al. (2021)	AI-enabled adherence monitoring app	PrEP adherence improvement	Smartphone mobile app	8-week follow-up with daily interaction	Single group (pilot)
Massa et al. (2023)	AI chatbot	PrEP demand creation and linkage to care	Facebook Messenger chatbot	On-demand (user-initiated, no fixed duration)	Peer educator outreach through Instagram, WhatsApp, and Facebook
Ni et al. (2025)	AI chatbot	HIV self-testing promotion	MYHIV365 web-based chatbot (mobile and desktop)	On-demand (user-initiated, no fixed duration)	Single group (usability study)

Note. n =7. AI = artificial intelligence; PrEP = pre-exposure prophylaxis.

challenge of sustaining user motivation in longitudinal digital health interventions.

Feasibility and reach were consistently demonstrated across diverse SGM subgroups and recruitment channels, underscoring the scalability of AI-based models. Notably, one study reported that usability was unaffected by literacy or education level, suggesting equitable design and accessibility (Dos Santos et al., 2024). Collectively, these findings highlight AI's strong translational potential for HIV prevention while emphasizing the need for sustained engagement strategies and attention to ethical and equity considerations in future implementations.

Discussion

Our review is one of the first to synthesize quantitative evidence on AI-based HIV prevention interventions specifically targeting SGM populations. By distinguishing AI-enabled systems from conventional digital tools, our review provides a clearer understanding of how algorithmic personalization, adaptive feedback, and automated conversational support may contribute to HIV prevention outcomes. Rather than treating AI as a homogeneous category, the synthesis highlights the diverse ways in which AI mechanisms operate and where current evidence remains limited, preliminary, and heterogeneous. Given the early stage of this field, variation in study design and rigor was expected. The tiered framework applied in our review was therefore essential for differentiating between trials capable of estimating effectiveness (Tiers 1–2) and feasibility-focused designs (Tier 3) that inform implementation potential rather than causal impact.

Effectiveness Outcomes

Across studies, AI-based interventions demonstrated promising but still emerging effects on HIV testing uptake, PrEP adherence, and risk reduction behaviors. It is important that only two Tier 1 RCTs were identified, limiting confidence in causal inference.

Regarding HIV testing, AI-assisted chat interfaces were associated with high rates of HIV self-testing. These

Table 4. **Outcomes and Main Results of the Included Studies**

Study ID (Author, Year)	Primary Outcomes (Effectiveness)	Secondary Outcomes (Mechanisms and Mediators)	Implementation and Acceptability Outcomes	Key Findings/ Interpretation	Direction of Effect[a]
Buchbinder et al. (2023) *N* = 100 (intervention = 66, control = 34)	PrEP adherence: No significant between-group differences in TFV-DP levels from weeks 6 to 24 HIV testing uptake and risk reduction behaviors: NR	AI mechanisms: AI dosing verification accuracy high (85.3–91%, κ = 0.61–0.66) Other secondary outcomes: NR	Engagement: App use declined over time, but 70% reported greater likelihood of daily PrEP use Acceptability: high usability (SUS median = 80); 91.7% satisfied, 96.6% would reuse Feasibility: sustained app engagement across 24 weeks	AI-enhanced adherence monitoring accuracy but did not translate to improved behavioral adherence	Neutral
Cheah et al. (2024) *N* = 14 (single group)	NR	NR	Engagement: sustained engagement: 79% intended continued use Acceptability: high usability (SUS = 76.1 ± 8.2); satisfaction 8.6/10; 93% perceived usefulness Feasibility: fully accessible through mobile; 100% completion in beta testing	Demonstrated high usability and sustained engagement among MSM despite limited behavioral evaluation	Positive (implementation)
Christensen et al. (2013) *N* = 921 (Intervention = 437, Control = 484)	Risk reduction behaviors: reduced unprotected anal intercourse at 3-month follow-up (indirect effect through reduced shame) HIV testing uptake and PrEP outcomes: NR	Psychological mediator: Reduced sexual shame predicted decreased risky behavior	Engagement: high retention (*n* = 437) implies strong engagement Acceptability: high inferred acceptability through completion rate Feasibility: demonstrated online delivery feasibility among MSM youth	AI-driven game effectively reduced sexual risk behaviors through psychosocial mechanisms	Positive
Dos Santos et al. (2024) *N* = 210 (single-group)	NR	NR	Engagement: not quantitatively measured Acceptability: high usability (PSSUQ = 3.96; Health-ITUES = 4.26) Feasibility: accessible across literacy levels;	Demonstrated equitable usability and technical feasibility; limited behavioral outcome data	Positive (implementation)

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Table 4. (*continued*)

Study ID (Author, Year)	Primary Outcomes (Effectiveness)	Secondary Outcomes (Mechanisms and Mediators)	Implementation and Acceptability Outcomes	Key Findings/ Interpretation	Direction of Effect[a]
			210 youth completed app-based activities		
Liu et al. (2021) *N* = 20 (single-group)	PrEP adherence: median 91% adherence confirmed by AI-based dose verification; 84% said the app supported adherence HIV testing and risk reduction behaviors: NR	AI mechanisms: high detection accuracy—algorithm visually confirmed 80% of expected doses Other secondary outcomes: NR	Engagement: high engagement (68% would recommend; 84% would reuse) Acceptability: excellent usability and satisfaction (95–100% positive ratings) Feasibility: functioned effectively across racially diverse young MSM (75% African American, 25% Latino)	Strong adherence outcomes and high user satisfaction demonstrated proof-of-concept feasibility	Positive
Massa et al. (2023) *N* = 130 (single-group)	PrEP outcomes: chatbot contributed 17.4% of total project initiations suggesting lower conversion but extended reach HIV testing and risk reduction behaviors: NR	NR	Engagement: moderate (61.1% completed ≥1 chat; mean session ≈ 15 min) Acceptability: very high (most users rated usability 9-10/ 10) Feasibility: implemented across three cities; higher engagement among transgender girls and educated users	Chatbot expanded reach to hard-to-reach groups and maintained engagement with moderate conversion to PrEP initiation	Positive
Ni et al. (2025) *N* = 334 (single-group)	HIV testing uptake: high—66.2% ordered self-testing kits PrEP outcomes: 25.7% discussed PrEP; 16.5% requested clinic information Risk reduction behaviors: NR	AI mechanisms: chatbot generated 67.8% of total dialog, reflecting active conversational role Other secondary outcomes: NR	Engagement: high—average session 1–5 min (77%); 91% single use, 9% repeat use Acceptability: very high (92.5% positive feedback; mean recommendation score = 8.4/10) Feasibility: national reach through web-based platform	Web-based chatbot effectively increased HIV self-testing uptake and maintained strong engagement nationwide	Positive

Note. n =7. AI = artificial intelligence; Health-ITUES = Health Information Technology Usability Evaluation Scale; NR = not reported; PrEP = preexposure prophylaxis; PSSUQ = Post-Study System Usability Questionnaire; SUS = system usability scale; TFV-DP = tenofovir diphosphate. [a]Direction of effect: positive = improvement in behavioral or clinical outcomes; neutral = no significant effect; positive (implementation) = favorable findings in feasibility, acceptability, or engagement in the absence of demonstrated effectiveness outcomes.

findings suggest that conversational AI may reduce stigma-related barriers by providing discreet, on-demand, and identity-affirming support (Van Heerden et al., 2023). However, the modest rates of repeat testing observed indicate that initial engagement may not translate into sustained long-term preventive behaviors. This pattern mirrors broader challenges in digital health interventions, where early uptake often declines over time (Boucher & Raiker, 2024). It is important that findings from single-arm usability studies should be interpreted as hypothesis generating rather than conclusive.

The evidence for the role of AI in promoting PrEP adherence is mixed and may reflect differences in intervention design, study rigor, and efficacy. From a rigorously designed trial, AI-supported adherence tools consistently improved measurement precision but showed limited independent effects on adherence behavior (Buchbinder et al., 2023). This indicates that AI improves measurement precision but does not independently address motivational determinants of adherence. These findings align with prior reviews showing inconsistent effects of digital interventions on sustained PrEP use (Du et al., 2025).

By contrast, less rigorous pilot studies that combined PrEP adherence reminders, tracking, and supportive communication suggested more favorable adherence outcomes (Liu et al., 2021). This finding highlights potential social–cognitive mechanisms: conversational AI elements may simulate social presence, enhancing perceived support and self-regulation (Van Heerden et al., 2023). Together, these studies indicate that AI-based intervention effectiveness may depend on integrating algorithmic precision with behavioral theory–driven features, such as motivational messaging or supportive accountability.

Evidence for sexual risk reduction was limited to a single Tier 1 randomized controlled trial, which demonstrated reductions in condomless sex mediated by decreased sexual shame (Christensen et al., 2013). Although preliminary, this finding highlighted AI's potential to address stigma-related psychosocial drivers of HIV risk among SGM populations (Layland et al., 2020). However, as this finding is drawn from a single study, it should be interpreted as exploratory rather than confirmatory.

Mechanisms and Mediators

Evidence on the behavioral and psychosocial mechanisms underlying AI-based HIV prevention among SGM remains limited but conceptually promising. Across studies, AI technologies functioned as adaptive systems that tailored feedback, reminders, and motivational cues based on user data. This adaptive functionality aligns with Social Cognitive Theory (Bandura, 2012) and the COM-B model (Michie et al., 2011), reinforcing self-monitoring and perceived capability through data-driven feedback loops.

For example, Buchbinder et al. (2023) demonstrated that an AI-enabled adherence tool achieved high concordance with pharmacologic verification, offering real-time, objective feedback to participants and clinicians. Although behavioral gains were modest, this represents a new precision-based approach to reinforcing adherence behaviors. Similarly, chatbot interventions used NLP to sustain empathetic, responsive conversations, exemplifying how conversational AI can enhance engagement and motivation through perceived social presence (Ni et al., 2025).

These findings align with broader evidence indicating that AI enhances HIV prevention predominantly through high-fidelity precision and data-driven support rather than direct motivational influence. A recent global review of AI applications in HIV care highlighted that machine learning algorithms consistently outperform human judgment and standard clinical practices across various domains, achieving up to 100% sensitivity and 98.8% specificity in HIV self-test interpretation (Ngcobo et al., 2025). However, the proposed mechanisms from our review remain preliminary and hypothesis generating, given the small number and heterogeneity of studies.

Although none of the included studies formally tested psychosocial mediators, theory suggests several plausible pathways through which AI features might affect HIV-preventive behaviors. Personalization and predictive tailoring may increase perceived relevance and risk salience, whereas real-time feedback and monitoring promote self-regulation and habit formation (An & Ngo, 2025; Chaturvedi et al., 2025). Conversational AI may simulate social presence and supportive feedback, reducing perceived stigma and increasing self-efficacy for prevention behaviors (Chaudhry & Debi, 2024). Future trials should therefore embed explicit mediator measures (knowledge, perceived risk, self-efficacy, stigma, and social support) and use formal mediation analysis to determine whether these constructs explain intervention effects.

Implementation and Acceptability Outcomes

AI-based interventions across diverse platforms consistently demonstrated high engagement, acceptability, and feasibility among SGM populations, suggesting strong translational potential. However, heterogeneity in delivery channels, AI sophistication, and study contexts reveals important nuances that warrant discussion.

High acceptability across AI platforms and SGM subgroups supports the feasibility of deploying AI-driven digital tools at scale. These findings are consistent with broader evidence on technology-assisted HIV prevention and care in the general population, where diverse platforms, such as social media, hotlines, mobile apps, and chatbots, have been successfully deployed (Kamulegeya et al., 2025). Notably, equitable usability, which is unaffected by literacy or education differences (Dos Santos et al., 2024), points to AI's potential to reduce digital divides, an important equity consideration. These results further align with previous systematic reviews reporting high feasibility and acceptability of technology-assisted HIV testing interventions, as well as positive user appraisals (Horvath et al., 2020).

Notably, feasibility and usability studies may overestimate acceptability, engagement, and other implementation outcomes due to small, self-selected samples, lack of control groups, intensive researcher support, and short follow-up time time frames. These factors can inflate positive impressions that fail to generalize to real-world settings. Thus, the consistently high ratings in Tier 3 studies warrant cautious interpretation as preliminary signals, not definitive evidence of sustained engagement or scalability.

Sustained yet declining app engagement in longitudinal adherence monitoring interventions highlights the challenge of maintaining user motivation over time. Both Buchbinder et al. (2023) and Ni et al. (2025) observed high initial engagement that waned during follow-up, likely due to fading novelty effects and early enthusiasm. This pattern reflects a broader issue in digital health interventions, where initial uptake does not always translate into sustained behavior change (Boucher & Raiker, 2024). These findings emphasize the need for future interventions to integrate algorithmic precision with theory-driven engagement strategies, such as reinforcement learning or peer-simulated interactions, to promote long-term adherence.

Despite the generally high level of engagement and acceptability observed across AI-based interventions, ethical and equity considerations remain critical. The reliance on user-generated data and algorithmic prediction introduces potential risks, including privacy breaches, data misuse, and algorithmic bias, particularly when training datasets underrepresent diverse SGM subgroups (Van Heerden et al., 2023; Zhang & Zhang, 2023). These risks are especially salient given that most interventions demonstrated strong usability and reach (Buchbinder et al., 2023; Ni et al., 2025), highlighting that technical success alone does not ensure equitable impact on health outcomes. To optimize both effectiveness and equity, future AI-driven HIV prevention tools should be co-created with the communities of intended use, incorporate culturally sensitive natural language processing models, and be governed by transparent frameworks, ensuring that high engagement and acceptability lead to safe, equitable, and sustainable outcomes for all SGM populations.

Strengths and Limitations

Our review's strengths include rigorous adherence to PRISMA guidelines, explicit classification of AI modalities, and the use of multiple risk-of-bias tools appropriate for study design. The integration of implementation, mechanistic, and effectiveness data enhances interpretability.

However, several limitations must be acknowledged. First, substantial heterogeneity across studies, including differences in AI design (e.g., chatbots and predictive algorithms), target populations (i.e., MSM, transgender women, and other SGM subgroups), delivery formats (e.g., mobile apps, web platforms), and outcome measurement limits the comparability of findings. Second, the small number of rigorously designed RCTs and reliance on feasibility, pilot, or quasi-experimental studies constrain confidence in causal inference and generalizability. Third, most studies were conducted in the United States, Brazil, or Malaysia, limiting geographic generalizability. Fourth, our review did not impose age restrictions for study inclusion, resulting in a heterogeneous age range of participants across studies. This limits the ability to draw conclusions about age-specific effects. Finally, the limited measurement of behavioral mediators restricts the understanding of how AI-specific features translate into behavior change, and the small sample size prevented meaningful assessment of publication bias.

Implications

Although AI-driven interventions may enhance personalization and engagement in HIV prevention, their effectiveness remains uncertain due to the limited number of rigorous trials and heterogeneity in intervention design and outcome measures. Advancing this field will require adequately powered RCTs that isolate the added value of AI components relative to non-AI digital comparators. Future studies should embed explicit behavioral theory identified mediators (i.e, motivation, self-efficacy, and stigma reduction) to clarify how the interventions produce their effects and employ objective outcome measures where possible to reduce self-report bias and strengthen the rigor and reproducibility of finding. Clear reporting of AI algorithms, inputs, and decision pathways will be essential to advance transparency and reproducibility of the study results.

The findings of our review highlight several important implications for nursing practice. First, nurses can leverage AI-based tools as scalable extensions of nurse-led HIV prevention services. Rather than replacing clinical care, these technologies function as adjuncts that enhance outreach, provide timely personalized information, and reinforce prevention behaviors beyond traditional clinical encounters. Second, the strong acceptability and engagement observed across studies suggest that nurses are well positioned to integrate AI-enabled interventions into routine prevention workflows, such as facilitating HIV self-testing distribution and supporting PrEP initiation.

Implications for nursing education include the need to prepare nurses to critically appraise AI-enabled digital health tools, engage patients in technology-supported prevention strategies, and address ethical considerations such as data privacy and patient trust. Integrating foundational AI literacy into prelicensure nursing curricula may strengthen nurses' capacity to participate in the selection, implementation, and evaluation of digital HIV prevention interventions.

From an implementation standpoint, integrating AI tools into community-based HIV services may expand reach and reduce provider burden, but only if concerns about privacy, cultural appropriateness, and algorithmic fairness are proactively addressed. These implementation priorities are especially important given the limited geographic diversity and exploratory nature of the current evidence. Nurse researchers are well positioned to lead future studies that evaluate the real-world effectiveness, equity, and sustainability of AI-enabled HIV prevention strategies across diverse care settings.

Conclusion

AI-based digital interventions represent a promising, early-stage approach to HIV prevention for SGM populations. Current evidence indicates potential strengths in personalization, adaptive engagement, and scalable delivery, which may enhance traditional behavior-change strategies. However, the evidence remains limited, heterogeneous, and methodologically diverse, with mechanistic pathways incompletely understood. Our findings underscore the need for rigorously designed, adequately powered RCTs that explicitly assess behavioral mediators, compare AI-based with conventional digital interventions, and transparently report algorithmic features.

Disclosures

The authors report no real or perceived vested interests related to this article that could be construed as a conflict of interest.

Data Accessibility Statement

No new data were used; therefore, data sharing is not applicable.

Author Contributions

All authors on this paper meet the four criteria for authorship as identified by the International Committee of Medical Journal Editors; all authors have contributed to the conception and design of the study, drafted or have been involved in reviewing this manuscript, reviewed the final version of this manuscript before submission, and agree to be accountable for all aspects of the work. Specifically, using the CRediT taxonomy, the contributions of each author are as follows: Conceptualization & Methodology: P. Krongtham, R. Thato, E. P. H. Choi, R. Jantarapakdee, T. Van Nhat; Formal Analysis: P. Krongtham, R. Jantarapakdee, T. Van Nhat; Funding Acquisition: P. Krongtham; Investigation: P. Krongtham, R. Jantarapakdee, T. Van Nhat; Supervision: R. Thato, E. P. H. Choi; Resources: P. Krongtham; Data Curation: E. P. H. Choi; Writing—Original Draft: T. Van Nhat; Writing/Revising—P. Krongtham, R. Thato, E. P. H. Choi, R. Jantarapakdee, T. Van Nhat.

Key Considerations

- AI-based HIV prevention tools show strong acceptability and feasibility among SGM populations, with consistently high usability scores and satisfaction across studies. Clinicians can consider integrating AI tools, particularly chatbots and mobile apps, as supportive adjuncts to routine prevention services.
- AI-driven chatbots appear to be the most effective at promoting key HIV prevention behaviors, including HIV testing uptake and PrEP initiation. These tools may help clinicians reach individuals who avoid in-person services due to stigma, limited access, or scheduling barriers.
- Current evidence is promising but limited by small sample sizes and short follow-up periods, underscoring the need for clinicians to use AI interventions as complementary supports until more rigorous trials confirm their long-term behavioral effectiveness.

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