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Artificial Intelligence in Nursing Practice for HIV Prevention and Gender Equality in Uzbekistan: A Systematic Review and Predictive Modeling within SDG 3 and SDG 5

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Systematic Review

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Abstract

Background.

The Eastern Europe and Central Asia region has experienced the steepest global rise in new HIV infections since 2010. Uzbekistan faces compounding challenges: low HIV literacy, entrenched stigma among healthcare workers, and a critical shortage of infectious disease specialists that necessitates greater reliance on community nurses. Artificial intelligence (AI) and mobile health (mHealth) tools offer scalable solutions, yet evidence from nursing-led, community-based HIV prevention in this region is virtually absent from the international literature.

Methods.

We conducted a multi-stage mixed-methods study (2019–2025) combining: (1) a systematic literature review (SLR) of 1,021 peer-reviewed publications retrieved from Scopus, PubMed/MEDLINE, Embase, and CINAHL, supplemented by Russian-language databases (eLibrary.ru, CyberLeninka), (2) a cross-sectional survey of 1,367 community respondents and 688 nurses with validated bilingual instruments (Uzbek/Russian); (3) a quasi-experimental prospective cohort intervention (n = 500) deploying the nurse-led training programme "Let's Stop HIV Together" and the mHealth application "For Life / Hayot uchun" with pre-, post-, and 24-month follow-up assessment; and (4) a Random Forest predictive model (AUC 0.87, 95% CI: 0.84–0.90) to project HIV incidence scenarios through December 2026. All projections are accompanied by 95% confidence intervals derived from 1,000 bootstrap resamples.

Results.

The intervention produced statistically significant improvements across all 20 HIV knowledge and stigma indicators ($p < 0.001$). The most striking finding was a 9.0-fold increase in willingness to study alongside an HIV-positive classmate (from 9.7% to 86.9%). Nurse stigma was the second-strongest predictor of HIV risk behaviour in the predictive model (feature importance: 0.21), following low knowledge score (0.28). Without scaled-up intervention, the model projects the youth share of new HIV cases to reach 31.2% (95% CI: 28.7–33.6%) by end-2026. Scaling the platform to 5,000 community nurses is projected to reduce overall incidence to 7.1 (95% CI: 6.5–7.8) per 100,000 and avert an estimated 200 (95% CI: 156–244) infections annually, generating net health system savings of 357.5 million UZS per year and a return on investment of 2.8:1.

Conclusions.

AI-enhanced, nurse-led digital interventions represent a feasible, cost-effective, and contextually appropriate strategy for advancing SDG 3 (Good Health) and SDG 5 (Gender Equality) in Central Asia.

Prospective cluster-randomised validation is planned for 2026–2028 to confirm these findings.

1. Introduction

In 2015, the United Nations Member States adopted the 2030 Agenda for Sustainable Development, committing to 17 Sustainable Development Goals that represent an urgent call for action across a global partnership [1]. Among these, SDG 3 aims to "ensure healthy lives and promote well-being for all at all ages," with Target 3.3 specifically committing to ending the AIDS epidemic by 2030. SDG 5 aims to "achieve gender equality and empower all women and girls," recognising that gender inequality remains a persistent barrier to health access and outcomes worldwide [2].

The Eastern Europe and Central Asia (EECA) region has experienced a 49% increase in new HIV infections between 2010 and 2023 — the steepest rise globally [9]. In Uzbekistan, approximately 43,000 people were living with HIV as of 2021, with a concerning demographic shift: the proportion of new cases among youth aged 15–24 rose from 14% in 2010 and is projected to reach 29.5% in 2025 [10]. Despite national efforts, three critical barriers persist. First, HIV literacy remains critically low: only 20.1% of schoolchildren correctly identified that HIV is not transmitted through coughing in the 2019 baseline survey. Second, stigma is entrenched among healthcare workers, with 48% of surveyed nurses believing that HIV-positive patients require isolation in separate wards. Third, structural constraints are severe, with only 0.8 infectious disease physicians per 10,000 population, making a greater role for community nurses both necessary and appropriate [11].

Advancements in AI and mobile health technologies offer transformative potential for public health delivery in resource-limited settings. AI is increasingly applied to diagnosis, treatment recommendations, patient engagement, and administrative functions [6]. The World Health Organization's 2021 guidelines explicitly recommend digital health interventions, including mHealth tools and clinical decision-support systems, to improve the quality and reach of HIV prevention services [7, 8]. However, while AI applications in HIV research have grown — predominantly in biomarker discovery and drug development — their deployment within nursing-led, community-based prevention programmes in Central Asia has not been documented in the peer-reviewed literature.

This study addresses that gap. We ask: Can AI-enhanced, nurse-led HIV prevention interventions expedite the achievement of gender equality and health sustainability goals in Uzbekistan? We situate this question within an interdisciplinary framework that integrates nursing science, digital health, gender studies, and health economics, and adopt intersectionality [14] as a conceptual lens to analyse compounding barriers faced by women — both as providers and recipients of care.

2. Methodology

2.1 Systematic Literature Review

This SLR was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines [PRISMA 2020 checklist provided as Supplementary File 1]. The review protocol was prospectively registered on the PROSPERO international registry prior to data extraction. The review was conducted from data collected between January 2018 and 30 June 2024.

2.1.1 Search Strategy

To mitigate publication-language bias, we searched six electronic databases: Scopus, PubMed/MEDLINE, Embase, CINAHL, and two Russian-language databases — eLibrary.ru and CyberLeninka — the latter being essential given the Central Asian focus of the review and the predominance of Russian-language scientific publication in the post-Soviet space. Search strings used Boolean combinations of the following concept blocks: ("HIV prevention" OR "AIDS prevention") AND ("nurs*" OR "community health worker") AND ("artificial intelligence" OR "machine learning" OR "mHealth" OR "digital health") AND ("gender equality" OR "women's health" OR "stigma") AND ("Sustainable Development Goal" OR "SDG 3" OR "SDG 5"). Full search strings for each database are provided in Supplementary File 2.

The initial combined sample across all databases consisted of 2,743 records. After deduplication, 2,156 unique records were screened. English and Russian-language articles were eligible for inclusion. Records published in other languages were excluded, as translation resources were not available for the full-text review stage. This represents an acknowledged limitation. The screening and eligibility assessment were performed independently by all three authors using Rayyan systematic review software. Inter-rater reliability, measured using Cohen's kappa, was $\kappa = 0.81$ (95% CI: 0.76–0.86), indicating strong agreement. Disagreements were resolved through structured consensus discussion, with no third-party arbitration required. The final sample comprised 1,021 articles.

Articles were categorised into five thematic clusters (Table 1), with each article assigned to one primary cluster based on its principal contribution. Cluster assignments were made independently by two authors and verified by the third.

Table 1
System of Article Categorisation: AI-Enhanced Nursing in HIV Prevention and SDGs

Cluster	Thematic Markers	Keyword Examples
1: Gender Equality & HIV	Gender norms, women's health, HIV stigma, key populations	gender equality, women and HIV, stigma, discrimination, PrEP access
2: Health AI & Digital Interventions	AI, machine learning, mHealth, predictive modeling, chatbot	AI, machine learning, digital health, mobile app, predictive analytics, NLP
3: Sustainable Development Goals	SDG 3, SDG 5, 2030 Agenda, health equity, UHC	SDG 3, SDG 5, sustainable development, health policy, equity
4: Research Approaches	RCT, cohort study, mixed-methods, cost-effectiveness	cohort, randomised trial, meta-analysis, cost-effectiveness, qualitative
5: Geographical Focus	Central Asia, EECA, Uzbekistan, low-resource settings	Uzbekistan, Central Asia, EECA, low-income, community-based

2.2 Primary Data Collection

In addition to the SLR, we conducted a multi-stage mixed-methods study in Tashkent, Uzbekistan (2019–2025), approved by the Ethics Committee of Tashkent State Medical University (Protocol No. 08-16715, 13 June 2022) and conducted in accordance with the Declaration of Helsinki. Supplementary ethical approvals were obtained from the Tashkent City Department of Public Education and all participating institutions.

2.2.1 Study Design

- Cross-sectional survey (2019–2021): Assessment of HIV knowledge and stigma among three community population groups (n = 1,367) and nurses (n = 688).
- Prospective quasi-experimental cohort intervention (2019–2025): Implementation of the nurse-led programme "Let's Stop HIV Together" and the mHealth application "For Life / Hayot uchun" with pre-, post-, and 24-month follow-up evaluation (n = 500). A quasi-experimental rather than fully randomised design was selected given the ethical constraints of withholding an established educational intervention from schoolchildren; this limitation is discussed in Section 4. Attrition between baseline (n = 500) and 24-month follow-up (n = 434; 13.2% loss to follow-up) was analysed by comparing demographic characteristics of completers versus non-completers; no statistically significant differences were observed in age, gender, or baseline knowledge score (all $p > 0.10$), reducing the likelihood of attrition bias.
- Predictive simulation modelling (2025–2026): Development of a Random Forest machine learning model to project HIV incidence scenarios through December 2026 under two policy conditions (see Section 2.4).

2.2.2 Participants

Community respondents (n = 1,367) were divided into: Group I — Childhood and Adolescence (schoolchildren aged 14–18; n = 811); Group II — Youth (university students aged 18–29; n = 355); Group III — Mature and Middle Age (aged 30+; n = 201). Random cluster sampling was performed across 15 schools in all 11 districts of Tashkent. An additional online survey via smirkhamidova.com (n = 256) supplemented offline data collection; online participants were recruited via school-administered links, were required to confirm age eligibility, and IP-level duplicate screening was applied to minimise fraudulent responses. Self-selection bias among online respondents is acknowledged as a limitation.

Nurses (n = 688) were recruited from primary healthcare facilities (main group, n = 614) and specialised AIDS centres (control group for the nurse survey, n = 74), plus 28 head nurses for organisational assessment. The AIDS-centre nurses served as a knowledge-benchmark comparator rather than an intervention control group; these two roles are analytically distinct and reported separately.

2.2.3 Instruments

Structured questionnaires were developed in Uzbek and Russian and validated through a two-stage process: (1) expert content validity assessment by a panel of five infectious disease and public health specialists (Content Validity Index: 0.91); and (2) pilot testing with 30 respondents not included in the final sample, followed by item refinement. Internal consistency of the final instruments was satisfactory: Cronbach's α = 0.79 for the 19-item community questionnaire and α = 0.74 for the 11-item nurse questionnaire. For the general population, the instrument assessed HIV transmission knowledge, prevention awareness, and stigmatising attitudes. For nurses, the instrument evaluated HIV knowledge, willingness to provide care, and discriminatory attitudes.

2.2.4 Intervention

The training programme "Let's Stop HIV Together" was delivered through interactive seminars using ICT tools, illustrated booklets, and participatory exercises, conducted by trained nurses in school settings. The digital platform comprised the website smirkhamidova.com and the mobile application "For Life / Hayot uchun," featuring knowledge modules, a stigma self-assessment tool, and a rule-based virtual consultant. These components constituted the evaluated intervention (2019–2021). In 2024, a prototype large language model (LLM) chatbot was subsequently integrated into the platform as a future-facing enhancement; this component was developed and piloted after the close of the intervention evaluation period and its outcomes are not reflected in Table 4. Prospective evaluation of the LLM component is planned as part of the 2026–2028 cluster-RCT.

2.3 Statistical Analysis

Categorical outcomes were compared using Pearson's χ^2 test; continuous outcomes were compared using Student's t-test or ANOVA for repeated measures, as appropriate. Odds ratios (OR) with 95% confidence intervals (CIs) are reported throughout. The significance threshold was set at $\alpha = 0.05$. All inferential statistics were computed in SPSS v.26; confidence intervals for proportions were calculated using the Wilson score method to ensure validity at the distributional extremes.

2.4 Predictive Simulation Modelling

A Random Forest classifier (1,000 decision trees) was trained to predict the binary outcome "HIV risk behaviour" at the individual level, with input features: age group, gender, HIV knowledge score, stigma score of assigned primary care nurse, mHealth platform access, educational attainment, and geographic location (urban/peri-urban). The model was built on a combined dataset comprising 10,500 real data points from the primary study, augmented to 50,000 agents via Gaussian copula-based synthetic data generation to achieve sufficient statistical power for subgroup analyses. To evaluate the effect of augmentation on model performance, we compared AUC metrics between the real-data-only model (AUC 0.81, 95% CI: 0.76–0.86) and the augmented model (AUC 0.87, 95% CI: 0.84–0.90); the improvement reflects enhanced minority-class representation rather than data leakage, as confirmed by the consistent performance on the held-out real-data test set.

The model was validated on a temporally separated hold-out set (real data from 2023–2024, n = 1,847 observations not used in training), yielding sensitivity = 0.82 and specificity = 0.79. Prospective external validation on an independent cohort from regions outside Tashkent is planned for 2026–2027 and is a prerequisite before the model is used for clinical or administrative decision-making. All projections in Section 3.3 were generated by running the model across 1,000 bootstrap resamples of the agent population; 95% confidence intervals reflect the 2.5th and 97.5th percentiles of the resulting projection distributions. Model code and the synthetic dataset are publicly available at https://github.com/smirkhamidova/ForLife-AImodel (DOI: 10.5281/zenodo.XXXXXXX).

3. Results

3.1 Gender Equality and HIV Stigma in Nursing

Nursing in Uzbekistan is a predominantly female profession (over 95% of nurses are women), meaning that gender dynamics intersect directly with healthcare delivery. Our survey of 688 nurses revealed a significant gender dimension to HIV stigma: the most stigmatised care procedures were those related to women's reproductive health. Despite 96% (95% CI: 88.0–99.0%) of control-group nurses (specialised AIDS centres) being willing to measure blood pressure on an HIV-positive patient, only 51% (95% CI: 39.2–62.8%) were willing to assist in childbirth for an HIV-positive woman — the lowest willingness rate for any clinical task in that group (Table 2). In the main group (non-specialised facilities), childbirth assistance willingness was 59% (95% CI: 55.0–63.0%), with 25% (95% CI: 21.7–28.6%) of nurses reporting fear or anger when informed a patient is HIV-positive.

Table 2
Nurses' Willingness to Provide Care to HIV-Positive Patients (n = 688)

Question	Control Group (n = 74) % (95% CI)	Main Group (n = 614) % (95% CI)	p-value	χ^2
Must patients disclose HIV status to health workers?	68 (56.5–78.1)	59 (55.0–63.0)	0.11	2.57
Must relatives be informed of patient's HIV status?	18 (10.1–28.9)	46 (42.0–50.1)	**< 0.001**	17.9
Willing to measure blood pressure/pulse of HIV+ patient	96 (88.0–99.0)	89 (86.3–91.3)	**0.04**	4.15
Willing to perform injections/dressings for HIV+ patient	89 (79.7–94.8)	72 (68.3–75.5)	**< 0.001**	12.3
Willing to assist in childbirth for HIV+ woman	**51 (39.2–62.8)**	59 (55.0–63.0)	0.15	2.07
Believe HIV+ patients need separate wards	20 (11.9–30.9)	29 (25.5–32.7)	0.07	3.28
Willing to use shared toilet with HIV+ person	80 (69.2–88.2)	49 (45.0–53.1)	**< 0.001**	19.6
Will provide full medical care knowing patient is HIV+	97 (89.9–99.6)	77 (73.5–80.2)	**< 0.001**	14.9
Feel fear or anger knowing patient is HIV+	11 (5.2–20.4)	25 (21.7–28.6)	**< 0.001**	7.82

Note: 95% CIs calculated using the Wilson score method. Bold p-values indicate statistical significance at α = 0.05.

Table 3
Distribution of Survey Respondents by Age Group and Gender (n = 1,367)

Age Group	Female % (n)	Male % (n)	Total n	% of Sample
14–18 years (Group I)	58% (470)	42% (341)	811	59.3%
18–29 years (Group II)	62% (220)	38% (135)	355	26.0%
30 + years (Group III)	64% (129)	36% (72)	201	14.7%
Total	**60% (819)**	**40% (548)**	**1,367**	**100%**

3.2 Digital Intervention Outcomes

The training programme and mHealth application were implemented among 500 participants (87% students aged 14–18, 7% teachers, 6% parents) from two Tashkent schools. At baseline (2019), zero of the 20 indicators reached the 85%-correct threshold. By 24-month follow-up (2021), 12 of 20 indicators exceeded 85% correct responses (Table 4). All changes were statistically significant ($p < 0.001$).

Table 4
Knowledge and Attitude Changes Among Schoolchildren (n = 434, pre- vs. post-intervention)

Indicator	2019 Pre (%)	2020 Post (%)	2021 Follow-up (%)	Fold Change	p
HIV is not transmitted through coughing / sneezing	20.1	71.7	74.6	**3.5×**	< 0.001
HIV weakens the body's immune system	33.3	85.1	92.7	**2.8×**	< 0.001
An HIV+ mother can give birth to a healthy baby (with PMTCT)	12.6	45.7	49.4	**3.9×**	< 0.001
HIV can be transmitted through blood and sexual fluids	32.4	72.6	89.4	**2.8×**	< 0.001
HIV is not transmitted through casual contact / communication	20.1	77.4	81.2	**4.0×**	< 0.001
HIV infection cannot be cured (no vaccine)	20.1	86.9	85.3	**4.2×**	< 0.001
Positive HIV test ≠ AIDS diagnosis	10.1	49.8	58.0	**5.7×**	< 0.001
Would NOT refuse to study with an HIV+ classmate†	9.7	48.7	86.9	**9.0×**	< 0.001

† Indicator 20 is reversed: the percentage shown represents those who would NOT refuse (i.e., tolerant attitude). Full 20-indicator results are provided in Supplementary Table S1.

3.2.1 Predictive Model: Feature Importance

The Random Forest model identified the following ranked predictors of HIV risk behaviour (feature importance scores, mean decrease in Gini impurity):

Feature	Importance Score
Low HIV knowledge score	0.28
High nurse stigma score (assigned primary care nurse)	0.21
Absence of mHealth platform access	0.17
Age 18–24 years	0.14
Female gender in peri-urban / rural setting	0.09
Low educational attainment	0.06
Geographic remoteness (outside central districts)	0.05

3.3 Epidemiological Projections and SDG Alignment

According to official data from the Republican AIDS Centre, HIV incidence in Uzbekistan decreased from 14.6 per 100,000 population in 2009 to 8.4 in 2020. However, a disaggregated analysis reveals a concerning demographic shift toward younger populations (Table 5). Under the business-as-usual scenario (no scaled-up digital intervention), the model projects the youth share of new infections (ages 15–29) to reach 31.2% (95% CI: 28.7–33.6%) by end-2026 — a trajectory incompatible with meeting SDG Target 3.3 by 2030. The scale-up scenario — in which 5,000 community nurses are trained and equipped with the "For Life" AI-mHealth platform — projects an overall incidence reduction to 7.1 (95% CI: 6.5–7.8) per 100,000 and a youth share of 25.1% (95% CI: 22.8–27.5%).

Table 5
Age Distribution of New HIV Cases in Uzbekistan: Observed and Projected, 2015–2026

Year	0–19 yrs (% new cases)	20–29 yrs (% new cases)	30 + yrs (% new cases)	Total incidence per 100,000	Source
2015	7.8	18.2	74.0	10.2	Observed
2020	9.2	24.5	66.3	8.4	Observed
2023	11.5	27.0	61.5	8.1	Observed
2025 (projected, no scale-up)	13.1	29.5 (27.1–31.9)	57.4	7.9 (7.3–8.5)	Modelled
2026 (projected, no scale-up)	14.8	31.2 (28.7–33.6)	54.0	8.2 (7.6–8.9)	Modelled
2026 (projected, with AI+mHealth scale-up)	11.2	25.1 (22.8–27.5)	63.7	7.1 (6.5–7.8)	Modelled

Note: Parenthetical values are 95% CIs from 1,000 bootstrap resamples. Observed data from Republican AIDS Centre [10]; *projected values from the Random Forest simulation model. Scale-up scenario assumes training of 5,000 nurses and platform deployment across all 14 regions of Uzbekistan.*

3.4 Cost-Effectiveness Analysis

The economic evaluation follows a budget-impact analysis framework, comparing direct medical costs under two scenarios over a one-year horizon (2026). We do not claim this constitutes a full health-technology assessment; a formal cost-utility analysis reporting cost per DALY averted is planned as part of the prospective cluster-RCT protocol and will be reported separately. The 200 averted infections (95% CI: 156–244) used as the key parameter in Table 6 are derived from the bootstrapped projection distributions described in Section 2.4.

Indirect costs, including nurse time allocated to training (estimated at 16 hours per nurse at an opportunity cost of approximately 55,000 UZS per nurse, totalling 275 million UZS for 5,000 nurses), are excluded from Table 6 as they are not captured in direct health system expenditure accounts. Their

inclusion would reduce the net saving to approximately 82.5 million UZS per year, maintaining a positive return on investment. Sensitivity analysis across a ± 30% range of key cost parameters is provided in Supplementary File 3.

Table 6
Projected Budget Impact of AI-Enhanced Nurse-Led Intervention (2026 Horizon, Million UZS)

Cost Item	Scenario A: No Intervention	Scenario B: AI + mHealth Scale-Up (5,000 nurses)
Treatment costs for 200 averted new HIV cases (95% CI: 156–244) × 1.82M UZS	364 (284–444)	0 (prevented)
Treatment of 5 averted occupational nurse infections × 39M UZS	195	0 (prevented)
Training 5,000 nurses	0	65
AI platform development (one-time)	0	65
Annual mHealth platform maintenance	0	6.5
Differentiated training programme development	0	65
Total direct system cost	**559 (479–639)**	**201.5**
Net annual direct saving	—	**357.5 (277–438)**

Note: All cost parameters are expressed in millions of Uzbekistani Som (UZS) at 2025 prices. Parenthetical values propagate the 95% CI of averted infections. A formal cost-utility analysis is planned for the 2026–2028 prospective study phase. Sensitivity analysis is provided in Supplementary File 3.

4. Discussion

Our findings indicate that a relatively low-cost, nurse-led digital intervention can produce substantial improvements in HIV knowledge and stigma reduction among youth in Tashkent. The 9.0-fold increase in willingness to study alongside an HIV-positive classmate — sustained at 24-month follow-up — represents a clinically and socially meaningful shift in normative attitudes. This result aligns with Stangl et al. [44], who demonstrated that community interventions combining information, participatory methods, and contact with affected groups can shift stigmatising attitudes within short timeframes.

The predictive model identifies nurse stigma as the second-strongest individual-level predictor of HIV risk behaviour (feature importance: 0.21), after low knowledge score (0.28). This finding is particularly salient in the Uzbek context, where over 95% of the nursing workforce is female. Entrenched stigma among nurses does not only harm patients — it represents a professional development gap for a predominantly female workforce and undermines the SDG 5 goal of investing in women's economic participation and empowerment. Equipping nurses with digital decision-support and anti-stigma training is therefore simultaneously a public health intervention and a gender equality investment.

4.1 Limitations

This study has several limitations that should inform interpretation of findings and guide future research.

- Geographic scope: Data were collected in Tashkent and may not be representative of rural areas — particularly Karakalpakstan, the Fergana Valley, and Surkhandarya — where internet connectivity, digital literacy, and health system infrastructure differ substantially.
- Study design: The quasi-experimental design, adopted for ethical reasons, precludes definitive causal inference. We characterise our findings as "strong preliminary evidence" that the intervention is associated with improved outcomes, rather than proof of causation. A cluster-randomised controlled trial is planned for 2026–2028.
- Predictive model: The model relies on a feature set that does not include direct behavioural indicators of sexual risk (e.g., condom use, partner number), which are established primary drivers of transmission. These variables were excluded due to data sensitivity constraints. Additionally, external validation on populations outside Tashkent has not yet been conducted; the model should not be used for individual-level clinical risk assessment pending such validation.
- SLR language scope: Despite the inclusion of Russian-language databases, literature in Uzbek and other regional languages was not retrievable through the searched platforms, representing a residual language bias.
- Self-report bias: Stigma and knowledge were measured through self-report instruments, which are subject to social desirability bias, particularly in a context with high baseline stigma.

4.2 Policy Implications

The findings carry several actionable policy implications for Uzbekistan and the broader EECA region. First, the "For Life" mHealth platform should be integrated into the national HIV prevention strategy with dedicated funding for scale-up across all 14 regions. Second, continuous professional development on HIV stigma reduction should be mandated for all primary care nurses. Third, a national task force on gender equality in health AI should be established to ensure that digital tools are co-designed with and for women. Fourth, the predictive model should be prospectively validated and, upon confirmation, deployed to support data-driven resource allocation in HIV prevention.

In relation to the EU AI Act [29] — enacted in August 2024 and now in its phased implementation period — AI tools deployed in public health settings such as this may qualify as high-risk systems under Annex III (health and safety systems), triggering requirements for transparency, human oversight, and conformity assessment. Policymakers adopting the platform should account for these regulatory obligations, and international partners supporting digital health in Central Asia should incorporate such frameworks into their technical assistance.

5. Conclusions

This study provides, to our knowledge, the first comprehensive empirical evidence from Uzbekistan — and among the first from Central Asia — that AI-enhanced, nurse-led digital interventions can significantly improve HIV knowledge, reduce stigma, and offer a cost-effective pathway toward achieving SDG 3 and SDG 5 simultaneously. Key findings include a 3.2–9.0-fold improvement across knowledge and attitude indicators, nurse stigma identified as the second-strongest modifiable predictor of HIV risk behaviour, and a projected budget saving of 357.5 million UZS per year (95% CI: 277–438 million) under full scale-up.

Critically, these findings are characterised as strong preliminary evidence from a quasi-experimental study. Definitive causal confirmation awaits the planned 2026–2028 cluster-randomised trial. The predictive model, while demonstrating promising internal performance (AUC 0.87), requires prospective external validation before application to clinical or policy decision-making.

The integration of SDG 3 and SDG 5 within a single intervention framework — in which female nurses are simultaneously the agents and beneficiaries of technological empowerment — represents a novel contribution to the global health literature. These findings provide actionable evidence for policymakers in Uzbekistan and across the EECA region to invest in scalable, contextually adapted, AI-enabled nursing platforms as tools for achieving the 2030 Agenda.

Declarations

Author Contributions

Conceptualisation: S.M.M. and H.E.R. Data curation: S.M.M. Formal analysis: S.M.M. and G.K.K. Funding acquisition: S.M.M. Investigation: S.M.M., H.E.R., and G.K.K. Methodology: S.M.M. and H.E.R. Project administration: S.M.M. Resources: H.E.R. and G.K.K. Software: S.M.M. Supervision: S.M.M. Validation: S.M.M., H.E.R., and G.K.K. Visualisation: S.M.M. and G.K.K. Writing — original draft: S.M.M. Writing — review and editing: S.M.M., H.E.R., and G.K.K. All authors have read and agreed to the published version of the manuscript.

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Competing Interests

The authors declare no competing interests.

Ethics Approval

This study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Tashkent State Medical University (Approval No. 08-16715, 13 June 2022). Additional

approvals were obtained from the Tashkent City Department of Public Education and all participating schools and healthcare facilities.

Informed Consent

Informed consent was obtained from all participants. For participants under 18 years of age, written parental or guardian consent was obtained prior to enrolment.

Data Availability

The de-identified aggregate data underlying Tables 2–6 are available from the corresponding author upon reasonable request, subject to a signed data use agreement (contact: smirkhamidova@gmail.com). Individual-level data containing HIV-related attributes are not publicly available due to privacy protections under Uzbekistan law and the Declaration of Helsinki.

Code Availability

All analysis code, including SPSS syntax for inferential statistics and Python scripts for Random Forest model training, hyperparameter tuning, and bootstrap resampling, is deposited in the public repository.

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