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Non-medical drug use in Kenya and urban Ethiopia: a cross-sectional secondary analysis of Population-based HIV Impact Assessment surveys, 2017-2019

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ABSTRACT

Background: Non-medical drug use is an important public health concern in sub-Saharan Africa, but comparable population-based evidence remains limited. We assessed its prevalence, associated factors and predictive correlates in Kenya and urban Ethiopia.

Methods: We conducted a cross-sectional secondary analysis of Population-based HIV Impact Assessment data from Ethiopia (2017-2018) and Kenya (2018-2019). Complete-case analysis included participants aged 15-64 years. We estimated unweighted prevalence, fitted multivariable logistic regression models, and compared LASSO, random forest and XGBoost prediction models.

Results: Among 51,269 participants, overall unweighted prevalence of non-medical drug use was 6.4%, with 11.6% in urban Ethiopia and 3.1% in Kenya. Females had lower adjusted odds than males (aOR 0.21, 95% CI 0.19-0.22), while adults aged 30-34 years had the highest adjusted odds relative to those aged 15-19 years (aOR 3.87, 95% CI 3.32-4.53). Kenya participants had lower adjusted odds than those in urban Ethiopia (aOR 0.21, 95% CI 0.20-0.23). Secondary and tertiary education were associated with lower odds. HIV status was not retained in the final adjusted model. LASSO had the best held-out discrimination (test AUC 0.7804).

Conclusion: Non-medical drug use was concentrated among males and adults in early-to-middle adulthood and differed substantially between the survey samples. Targeted prevention and screening may be warranted, but country comparisons require caution because the Ethiopia

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and Kenya sampling frames differed and estimates were unweighted.

BACKGROUND

Non-medical use of psychoactive substances is an important public health concern because of its association with injury, mental ill-health, social harm and adverse infectious-disease outcomes. In this study, non-medical drug use refers to self-reported use of psychoactive substances for non-medical purposes, consistent with terminology used by the World Health Organization (WHO) and the Population-based HIV Impact Assessment (PHIA) programme.[1] Global drug use continues to increase; the United Nations Office on Drugs and Crime estimated that 331 million people used a drug in the past 12 months in 2024, with cannabis remaining the most widely used drug worldwide.[2]

Substance use among adolescents and adults in sub-Saharan Africa is heterogeneous and shaped by social, economic and environmental factors.[3] Poverty, adverse childhood experiences, stress and social exclusion may increase vulnerability to harmful substance use, although pathways vary across settings and substances.[4,5] Country-specific evidence also shows distinct patterns. In Kenya, injection drug use has important implications for HIV prevention,[6] while substance use has also been documented among healthcare professionals.[8] In Ethiopia, khat use is culturally embedded in some settings and has been reported among secondary-school students and other young populations.[7]

Large population-based datasets that permit comparable examination of non-medical drug use and HIV status in East Africa remain limited. The PHIA surveys provide standardised household survey and biomarker data, although the relevant sampling frames differed: EPHIA 2017-2018 represented urban Ethiopia, whereas KENPHIA 2018-2019 was a national household survey in Kenya.[9-11] We therefore aimed to estimate unweighted non-medical drug use within the analysed PHIA samples, identify demographic and socioeconomic factors associated with use, examine its relationship with HIV status, and explore the predictive performance of selected machine-learning models.

METHODS

Study design and data sources

We conducted a cross-sectional secondary analysis of PHIA data from EPHIA 2017-2018 and KENPHIA 2018-2019. PHIA surveys use multistage stratified cluster sampling and standardised household questionnaires and HIV biomarker testing.[9-12] EPHIA sampled households across urban Ethiopia, whereas KENPHIA sampled households nationally in Kenya.[9,10]

Study population and eligibility

The analysis included PHIA respondents aged 15-64 years with complete information on the outcome and covariates required for the reported analyses. The source datasets contained 67,868 records. Complete-case analysis excluded 16,599 records (24.5%), leaving 51,269 participants.

Outcome and covariates

The primary outcome was self-reported non-medical drug use during the preceding 12 months. Respondents were asked about substances including khat, hashish, glue (mastish), marijuana, cocaine, heroin and other drugs used for non-medical purposes; alcohol was assessed separately and was not included in the outcome.[12] The outcome was coded yes/no. Covariates reported in the final analyses were age group, sex, education level, wealth-index quintile, country/survey and HIV serostatus.

Data management and statistical analysis

Data management and analysis were conducted in R version 4.5.[13] Data were checked for duplicate records and internal inconsistencies, and variables were recoded to align with the study objectives.[14] Because PHIA survey weights were not applied in this secondary analysis, all prevalence estimates reported here are unweighted sample estimates and

should not be interpreted as nationally weighted population prevalence. Variance estimation accounted for clustering and stratification within the survey design.

Participant characteristics were summarised using counts and percentages. Bivariate associations were assessed using chi-square tests. Multivariable logistic regression was used to estimate adjusted odds ratios (aORs) and 95% confidence intervals (CIs), with statistical significance set at $p<0.05$.[15] The final adjusted model included age group, sex, education level, wealth-index quintile and country/survey. HIV status was evaluated but was not retained in the final adjusted model because it did not materially improve model performance.

For predictive modelling, Boruta was used to identify relevant features.[16] Three algorithms were compared: least absolute shrinkage and selection operator (LASSO) regression, random forest and extreme gradient boosting (XGBoost). Models used a 70:30 training-test split stratified by country and drug-use status. Hyperparameters were tuned by five-fold cross-validation within the training data. Discrimination was assessed using the area under the receiver operating characteristic curve (AUC) in the training and held-out test sets. Model-specific measures were used to describe variable importance.

Ethical considerations

The original PHIA surveys received ethical approval from the US Centers for Disease Control and Prevention institutional review board, Columbia University Medical Center and relevant national ethics and regulatory bodies in Ethiopia and Kenya. ICAP at Columbia University granted access to the anonymised PHIA datasets. The present secondary analysis used de-identified data and did not involve re-contact with participants. The original surveys obtained informed consent in accordance with their approved protocols and the principles of the Declaration of Helsinki.[9,10]

RESULTS

Participant flow and characteristics

Of 67,868 source records, 25,416 were from Ethiopia and 42,452 from Kenya. Complete-case exclusions comprised 5,249 Ethiopian records (20.7%) and 11,350 Kenyan records (26.7%). The final analytic sample therefore included 20,167 participants from Ethiopia and 31,102 from Kenya (Figure 1). Overall, 3,299 participants reported non-medical drug use and 47,970 did not.

Table 1 summarises the analytic sample. Women comprised 58.3% of participants, 34.6% were aged 15-24 years, and 4.2% were HIV-positive. The distribution of education and wealth differed between the two survey samples.

Prevalence of non-medical drug use

The overall unweighted prevalence of non-medical drug use was 6.4%. Prevalence was 11.6% in the urban Ethiopia sample and 3.1% in the Kenya sample (Figure 2). It was higher among males than females (11.0% vs 3.0%) and was highest in the 25-29-year age group (8.4%). HIV-negative participants had a prevalence of 6.5%, compared with 4.7% among HIV-positive participants. Prevalence varied non-linearly across education and wealth categories.

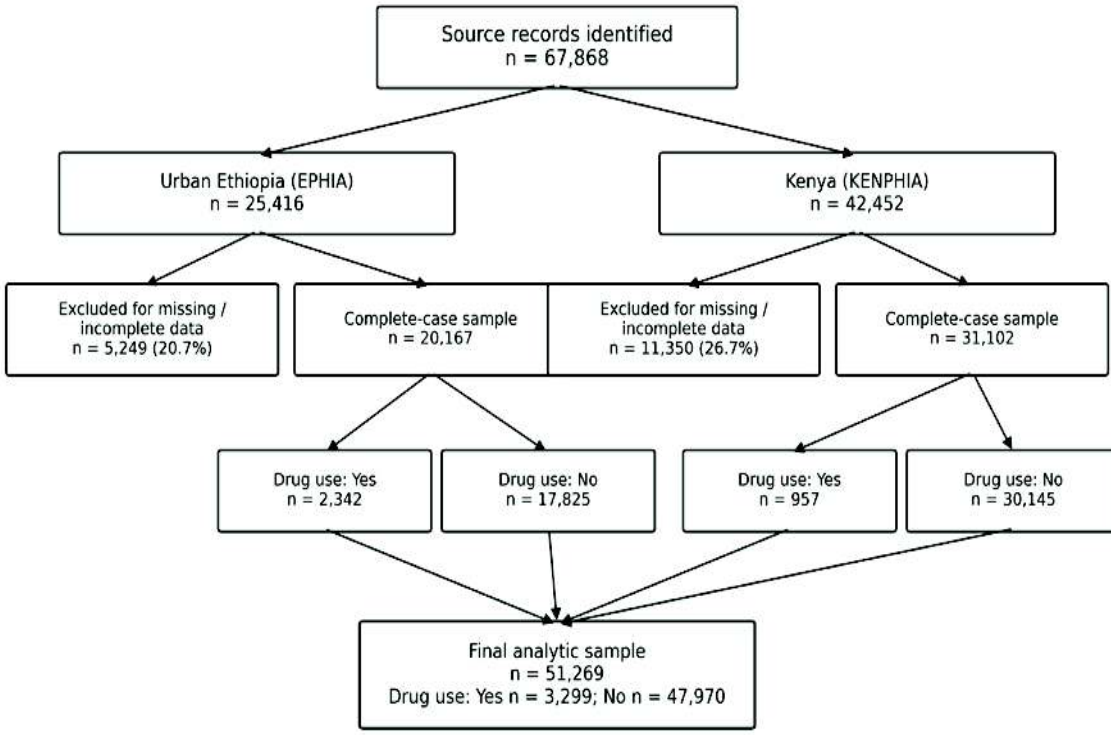
Factors associated with non-medical drug use

The adjusted model fitted the data better than the intercept-only model (likelihood-ratio chi-square=3547.4, df=18, $p<0.001$), and multicollinearity was low (maximum variance inflation factor 1.26). Compared with males, females had substantially lower odds of non-medical drug use (aOR 0.21, 95% CI 0.19-0.22; $p<0.001$). Relative to participants aged 15-19 years, adjusted odds increased through young adulthood and were highest among those aged 30-34 years (aOR 3.87, 95% CI 3.32-4.53; $p<0.001$). Participants in Kenya had lower adjusted odds than those in the urban Ethiopia survey sample (aOR 0.21, 95% CI 0.20-0.23; $p<0.001$).

Secondary education (aOR 0.81, 95% CI 0.72-0.91; p<0.001) and tertiary education (aOR 0.59, 95% CI 0.52-0.67; p<0.001) were associated with lower odds than no formal education; primary education was not independently associated with the outcome. The fourth wealth quintile had modestly higher odds than the poorest quintile (aOR 1.14, 95% CI 1.02-1.28; p=0.026). Full crude and adjusted estimates are provided in Supplementary Table S1 and displayed in Figure 3.

Predictive modelling

Sex and country/survey were the most influential predictors across the three predictive models (Supplementary Figure S2). LASSO showed the best held-out discrimination, with a training AUC of 0.7865 and test AUC of 0.7804. XGBoost had a training AUC of 0.8497 and test AUC of 0.7719, whereas random forest had a training AUC of 0.7453 and test AUC of 0.6504. Age-sex predicted-probability plots are provided in Supplementary Figures S1 and S3.



EPHIA, Ethiopia Population-based HIV Impact Assessment; KENPHIA, Kenya Population-based HIV Impact Assessment.

Figure 1. STROBE-style participant flow diagram for non-medical drug use analysis in urban Ethiopia (2017-2018) and Kenya (2018-2019).

Table 1. Characteristics of individuals from urban Ethiopia (2017-2018) and Kenya (2018-2019) included in the analysis of non-medical drug use

Characteristics	Urban Ethiopia (n=20,167)	Kenya (n=31,102)	Overall (n=51,269)
Wealth index quintile			
1	3516 (17.4%)	8095 (26.0%)	11611 (22.6%)
2	3625 (18.0%)	6820 (21.9%)	10445 (20.4%)
3	4006 (19.9%)	6544 (21.0%)	10550 (20.6%)
4	4351 (21.6%)	5741 (18.5%)	10092 (19.7%)
5	4669 (23.2%)	3902 (12.5%)	8571 (16.7%)
Age group			
15-19	4097 (20.3%)	5462 (17.6%)	9559 (18.6%)
20-24	3816 (18.9%)	4364 (14.0%)	8180 (16.0%)
25-29	3742 (18.6%)	4120 (13.2%)	7862 (15.3%)
30-34	2279 (11.3%)	4195 (13.5%)	6474 (12.6%)
35-39	2016 (10.0%)	3207 (10.3%)	5223 (10.2%)
40-44	1299 (6.4%)	2825 (9.1%)	4124 (8.0%)
45-49	925 (4.6%)	2206 (7.1%)	3131 (6.1%)
50-54	816 (4.0%)	1851 (6.0%)	2667 (5.2%)
55-59	590 (2.9%)	1534 (4.9%)	2124 (4.1%)
60+	587 (2.9%)	1338 (4.3%)	1925 (3.8%)
Education level			
None	2606 (12.9%)	8837 (28.4%)	11443 (22.3%)
Primary	7097 (35.2%)	7669 (24.7%)	14766 (28.8%)
Secondary	5783 (28.7%)	7550 (24.3%)	13333 (26.0%)
Tertiary	4681 (23.2%)	7046 (22.7%)	11727 (22.9%)
Sex			
Male	8012 (39.7%)	13351 (42.9%)	21363 (41.7%)
Female	12155 (60.3%)	17751 (57.1%)	29906 (58.3%)
HIV status			
Negative	19553 (97.0%)	29557 (95.0%)	49110 (95.8%)
Positive	614 (3.0%)	1545 (5.0%)	2159 (4.2%)
Drug use			
No	17825 (88.4%)	30145 (96.9%)	47970 (93.6%)
Yes	2342 (11.6%)	957 (3.1%)	3299 (6.4%)

Values are n (%) and are unweighted. HIV, human immunodeficiency virus.

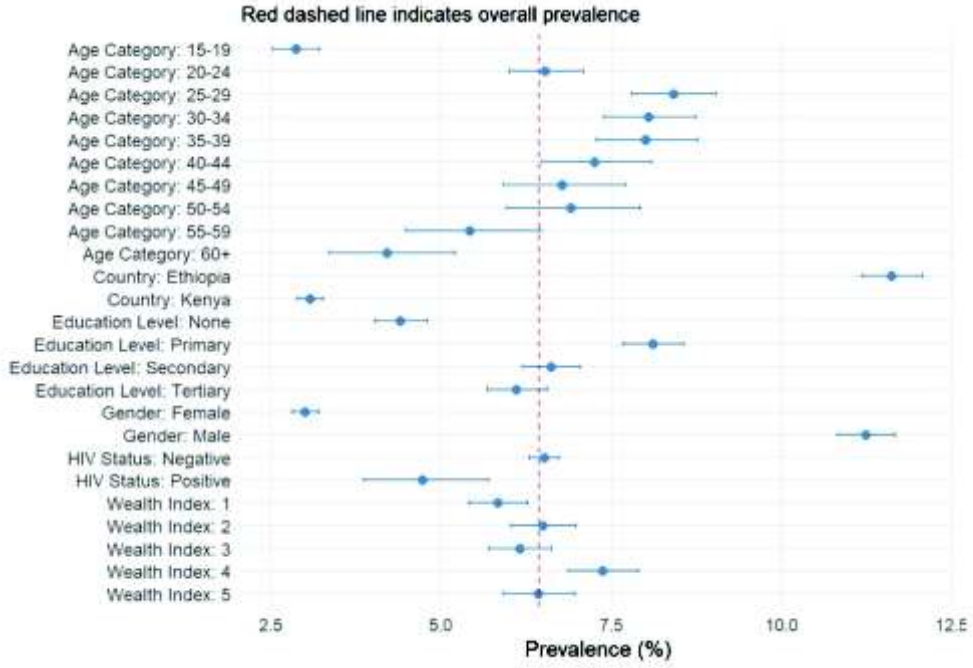


Figure 2. Unweighted prevalence of non-medical drug use in urban Ethiopia (2017-2018) and Kenya (2018-2019). The Ethiopia category represents the urban EPHIA sample; the dashed line indicates overall prevalence.

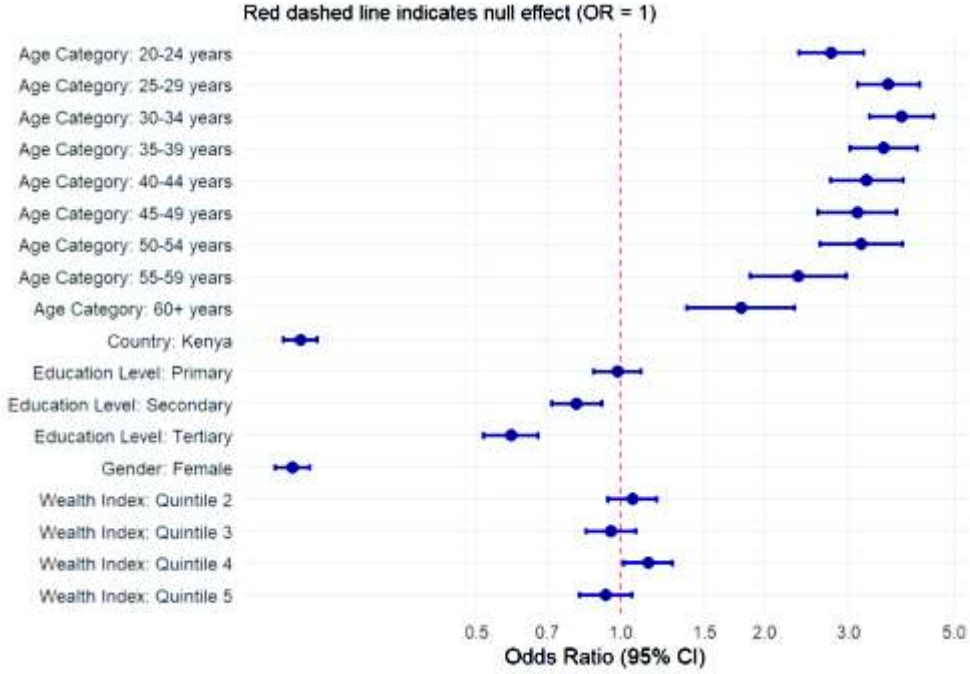
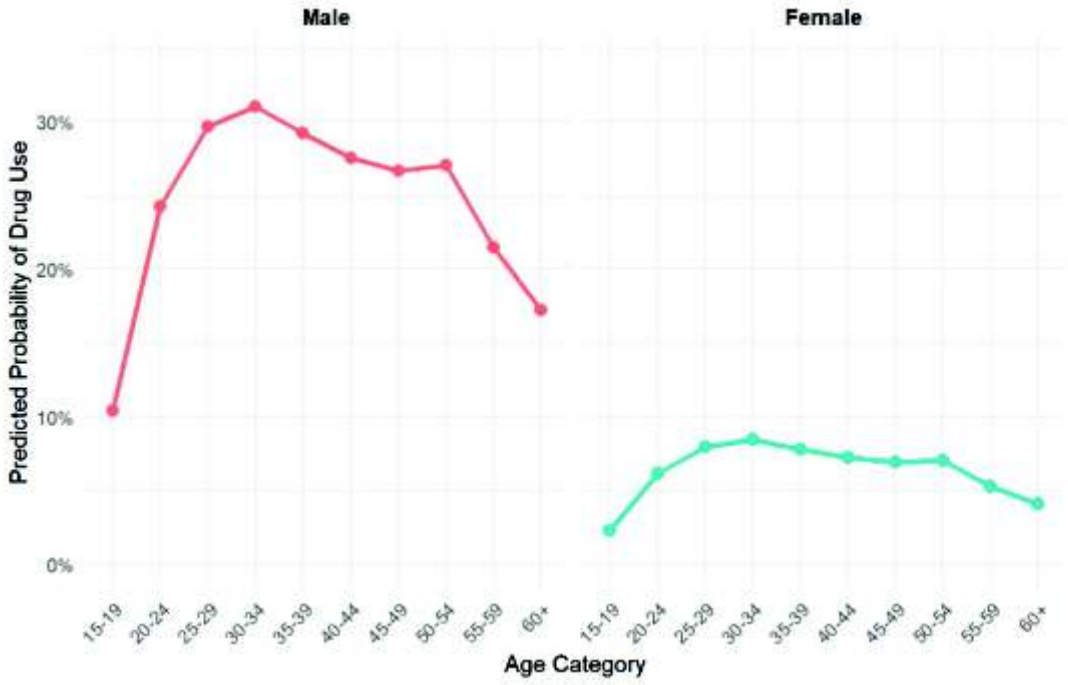
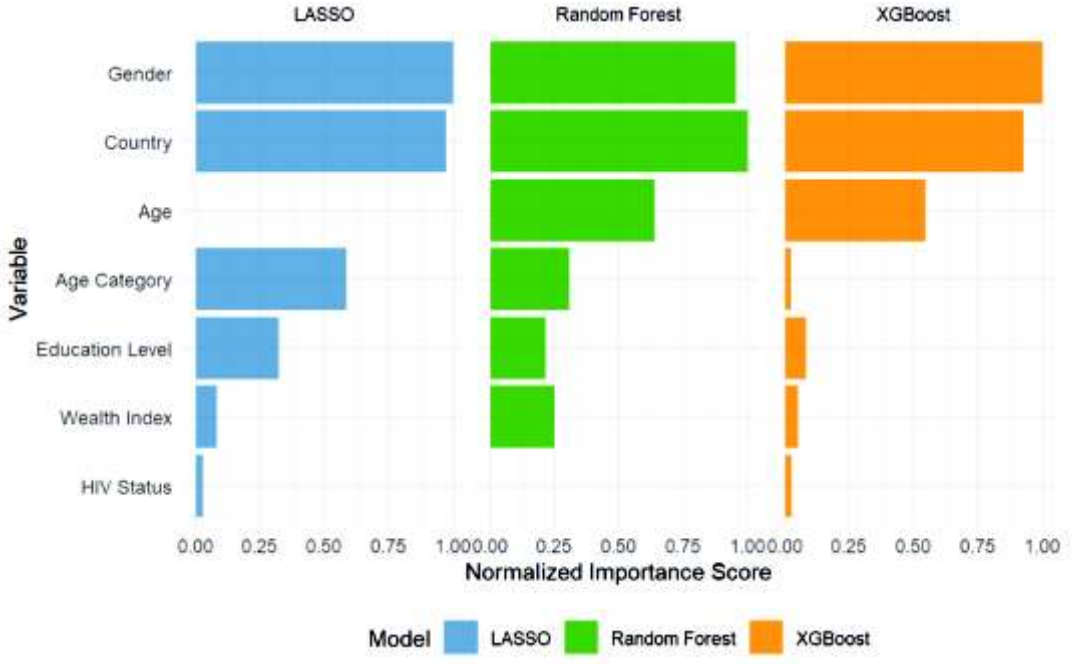


Figure 3. Adjusted odds ratios for factors associated with non-medical drug use in urban Ethiopia (2017-2018) and Kenya (2018-2019). Ethiopia/EPHIA is the reference survey for the country comparison; the dashed line indicates the null effect (OR=1).

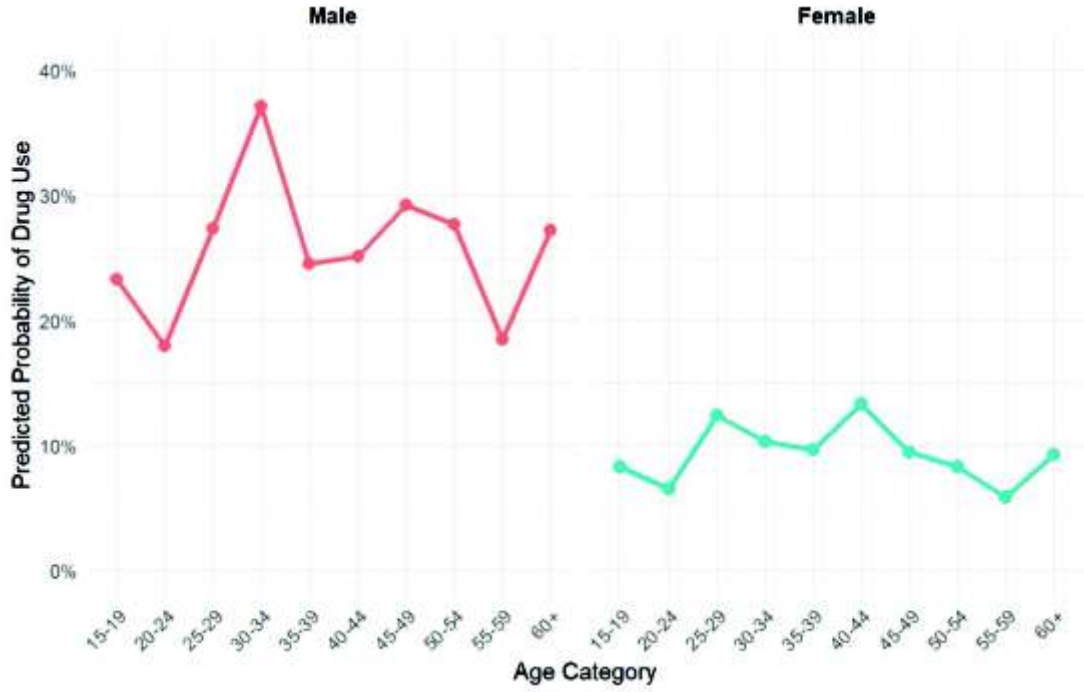
Supplementary material



Supplementary Figure S1. Age-sex stratified predicted probabilities of non-medical drug use based on logistic regression, urban Ethiopia (2017-2018) and Kenya (2018-2019).



Supplementary Figure S2. Variable importance for LASSO, random forest and XGBoost models predicting non-medical drug use in urban Ethiopia (2017-2018) and Kenya (2018-2019).



Supplementary Figure S3. Age-sex stratified predicted probabilities of non-medical drug use based on extreme gradient boosting, urban Ethiopia (2017-2018) and Kenya (2018-2019).

Supplementary Table S1. Crude and adjusted odds ratios for factors associated with non-medical drug use in urban Ethiopia (2017-2018) and Kenya (2018-2019)

Characteristic	Crude OR (95% CI)	p-value	Adjusted OR (95% CI)	p-value
Age Group				
15-19	1.00		1.00	
20-24	2.37 (2.04 - 2.75)	<0.001	2.76 (2.37 - 3.22)	<0.001
25-29	3.11 (2.70 - 3.60)	<0.001	3.64 (3.13 - 4.23)	<0.001

DISCUSSION

Principal findings

In this cross-sectional analysis of 51,269 PHIA participants, non-medical drug use differed markedly between the two survey samples and across demographic groups. Unweighted prevalence was 11.6% in the urban Ethiopia sample and 3.1% in Kenya. Male sex and young-to-middle adulthood were strongly associated with use, whereas secondary and tertiary education were associated with lower adjusted odds. HIV status was not retained in the final adjusted model. Among the predictive approaches, LASSO provided the best balance of test-set discrimination and parsimony.

Comparison with other studies and interpretation

The higher prevalence and adjusted odds among males are consistent with broader evidence from sub-Saharan Africa and with analyses of male

substance use in East Africa.[3,17] Age-related patterns also accord with evidence that substance-use disorders vary across the life course and are often concentrated in younger and middle adulthood.[18] These findings support prevention approaches that begin before peak-risk ages but continue beyond adolescence.

The large difference between Ethiopia and Kenya should be interpreted cautiously. Khat use is well established in parts of Ethiopia,[7] while Kenya has distinct drug markets and risk environments, including populations who inject drugs.[6] However, the country/survey indicator also captures important design differences: EPHIA represented urban Ethiopia, whereas KENPHIA was national.[9,10] The adjusted country estimate therefore cannot be interpreted as a pure national effect or as evidence that individual Ethiopians are intrinsically at greater risk than Kenyans.

Higher education was associated with lower adjusted odds, but this observational finding should not be interpreted as proof that education itself is protective. Education may act as a marker for multiple social and economic influences, and associations between educational attainment, socioeconomic position and substance use vary by population and substance.[19,20] Likewise, the modest increase in the fourth wealth quintile and the absence of a monotonic wealth gradient argue against a simple poverty-versus-affluence explanation.

The predictive analysis adds a complementary perspective to the regression findings. LASSO generalised better than the more complex models in the held-out data, which illustrates the potential value of parsimonious models when prediction is based on a limited set of demographic variables.[21,22] Nevertheless, the test AUC of approximately 0.78 indicates moderate rather than definitive discrimination, and the model has not undergone external validation. It should therefore be viewed as an exploratory risk-stratification model rather than a ready-to-deploy clinical or public-health tool.

Implications for policy and research

The concentration of non-medical drug use among males and adults in early-to-middle adulthood supports targeted prevention and screening in settings that reach these groups. Integration with existing HIV and primary-care platforms may be efficient where substance use is relevant to engagement in care; systematic-review evidence indicates that substance use can complicate progress along the HIV care continuum.[23] Screening, brief intervention and referral to treatment (SBIRT) has been implemented in African clinical settings and offers one potential service model.[24]

Prevention should also begin earlier in the life course. Evidence-based adolescent substance-use prevention and school-based resilience interventions may help build protective skills before peak-risk ages.[25,26] Any programme should be adapted to local drug markets and social context and linked to accessible mental-health and treatment services rather than relying on awareness campaigns alone.[29]

Strengths and limitations

Strengths include the large sample, standardised PHIA survey procedures, biomarker-confirmed HIV status and the combination of explanatory and predictive analyses. Several limitations are important. First, the cross-sectional design precludes causal inference. Second, substance use was self-reported and may be underestimated because of recall and social-desirability bias.[27] Third, 24.5% of source records were excluded in complete-case analysis, creating potential selection bias if missingness was not random. Fourth, the outcome combined several substances and did not support substance-specific or route-specific estimates; the findings therefore should not be extrapolated to people who inject drugs, who have distinct risk profiles.[28] Fifth, household surveys may under-represent people who are homeless, incarcerated or institutionalised. Sixth, the estimates are unweighted and the Ethiopia and Kenya

sampling frames differed substantially, limiting population-level and direct cross-country interpretation. Finally, the predictive models were internally evaluated only and require external validation.

CONCLUSION

Non-medical drug use in these PHIA samples was concentrated among males and adults in early-to-middle adulthood and differed substantially between urban Ethiopia and Kenya. Higher secondary and tertiary education were associated with lower adjusted odds, while HIV status was not an independent predictor in the final model. These findings support context-specific prevention, screening and referral approaches, but country comparisons should be interpreted in light of the different survey sampling frames and the use of unweighted estimates. Future research should use substance-specific measures, address missing data and sampling weights where appropriate, and externally validate predictive models before implementation.

What is already known on this topic

- Non-medical drug use varies by age and sex, with higher use commonly reported among males and younger adults.
- Social and economic context shapes substance-use patterns in sub-Saharan Africa.
- Substance use can intersect with HIV prevention and care, but comparable population-based evidence in East Africa remains limited.

What this study adds

- In unweighted PHIA samples, non-medical drug use was 11.6% in urban Ethiopia and 3.1% in Kenya.
- Female sex and higher education were associated with lower adjusted odds, while odds peaked in early-to-middle adulthood.
- LASSO achieved moderate held-out discrimination (AUC 0.7804), but sampling-frame differences and lack of external validation limit direct policy deployment.

Authors' contributions

WFN led manuscript drafting and, together with CA, conducted data management and analysis. CZ and EO contributed analytical advice, interpretation of findings and policy implications. All authors critically revised the manuscript and approved the final version.

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Competing interests

The authors declare that they have no competing interests.

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