

1 **Accuracy of self-reported HIV testing history and awareness of HIV-positive**
2 **status among people living with HIV in four Sub-Saharan African countries**

3
4 Yiqing Xia¹, Rachael M Milwid¹, Arnaud Godin¹, Marie-Claude Boily², Leigh F Johnson³,
5 Kimberly Marsh⁴, Jeffrey W Eaton², Mathieu Maheu-Giroux¹

6
7 **Affiliations:**

8 (1) Department of Epidemiology, Biostatistics, and Occupational Health, School of
9 Population and Global Health, McGill University, Montréal, QC, Canada

10 (2) MRC Centre for Global Infectious Disease Analysis, School of Public Health,
11 Imperial College London, London, United Kingdom

12 (3) Centre for Infectious Disease Epidemiology and Research, University of Cape
13 Town, Cape Town, South Africa

14 (4) Strategic Information Department, Joint UN Programme on HIV/AIDS
15 (UNAIDS), Geneva, Switzerland

16

17 **Correspondence:**
18 Mathieu Maheu-Giroux
19 mathieu.maheu-giroux@mcgill.ca

20

21

22 **Abstract**

23 **Background:** In many countries in Sub-Saharan Africa, self-reported HIV testing history
24 and awareness of HIV-positive status from household surveys are used to estimate the
25 percentage of people living with HIV (PLHIV) who know their HIV status. Despite
26 widespread use, there is limited empirical information on the sensitivity of those self-
27 reports, which can be affected by non-disclosure.

28 **Methods:** Bayesian latent class models were used to estimate the sensitivity of self-
29 reported HIV testing history and awareness of HIV-positive status in four *Population-*
30 *based HIV Impact Assessment* surveys in Eswatini, Malawi, Tanzania, and Zambia.
31 Antiretroviral (ARV) metabolites biomarkers were used to identify persons on treatment
32 who did not accurately report their status. For those without ARV biomarkers, the
33 pooled estimate of non-disclosure among untreated persons was 1.48 higher than those
34 on treatment.

35 **Results:** Among PLHIV, the sensitivity of self-reported HIV testing history ranged 96%
36 to 99% across surveys. Sensitivity of self-reported awareness of HIV status varied from
37 91% to 97%. Non-disclosure was generally higher among men and those aged 15-24
38 years. Adjustments for imperfect sensitivity did not substantially influence estimates of
39 of PLHIV ever tested (difference <4%) but the proportion of PLHIV aware of their HIV-
40 positive status was higher than the unadjusted proportion (difference <8%).

41 **Conclusions:** Self-reported HIV testing histories in four Eastern and Southern African
42 countries are generally robust although adjustment for non-disclosure increases

43 estimated awareness of status. These findings can contribute to further refinements in
44 methods for monitoring progress along the HIV testing and treatment cascade.

45 **Keywords:** Sensitivity; Bayesian latent class; self-report; testing behaviors; HIV
46 disclosure; HIV/AIDS

47

48 INTRODUCTION

49 Monitoring the HIV treatment and care cascade is central to the *Joint United Nations*
50 *Programme on HIV/AIDS*' (UNAIDS) objective of ending the AIDS epidemic as a public
51 health risk by 2030 (1). Routine tracking of population-level progress towards the
52 UNAIDS' 2020 90-90-90 and 2030 95-95-95 diagnostic, treatment, and viral load
53 suppression targets can guide public health initiatives and improve programmatic
54 efficiencies (2). However, estimating progress towards the first pillar of the targets –the
55 percentage of people living with HIV (PLHIV) who know their HIV status– is challenging.
56 In sub-Saharan Africa (SSA), where 67% of the 38 million PLHIV were estimated to
57 reside in 2019 (3), measures of awareness are typically constructed from data about
58 self-reported HIV testing behaviour or reported directly from nationally representative
59 household surveys (4-8).

60 Consideration of the potential for measurement bias is needed when interpreting self-
61 reported survey data. Studies have shown that self-reporting about sensitive
62 information, such as an individual's HIV testing history and HIV status, could be affected
63 by non-disclosure (6, 9, 10). For example, inconsistencies have been documented in
64 Kenya and Malawi between an individual's self-reported data and biomarkers for
65 metabolites of antiretrovirals (ARVs) and viral load suppression (5, 10). While previous
66 studies have sought to validate the accuracy of self-reported HIV status (10-12),
67 analyzing recent data on both non-disclosure of self-reported HIV testing history and
68 HIV status among PLHIV is key to improving the validity of these estimates.

69 Surveys that collect both self-reported information and ARV biomarkers can be used to
70 assess the accuracy of self-reported HIV testing histories and HIV awareness status. In
71 this study, Bayesian latent class models are used to estimate the sensitivity of self-
72 reported HIV testing history and awareness of HIV status among PLHIV based on the
73 presence of detectable ARVs (13).

74 **Methods**

75 **Study population**

76 The *Population-based HIV Impact Assessment* (PHIA) surveys are nationally
77 representative multistage household-based surveys designed to provide population-
78 level information on the burden of HIV disease and to document the progress of HIV
79 programs (14-17). All four PHIA surveys with available microdata on PLHIV aged 15+
80 years of age were included in our analysis: *Swaziland (Eswatini) HIV Incidence*
81 *Measurement Survey 2* (2015-2016), *Malawi PHIA* (2015-2016), *Tanzania HIV Impact*
82 *Survey* (2016-2017), and *Zambia PHIA* (2016).

83 **Self-reports and antiretroviral (ARV) status**

84 Participants who reported having ever received the results of any HIV test were
85 classified as *ever tested and received results* (hereafter referred to as “*ever tested*”; see
86 *Table S1*). Participants who reported having received a positive test result after any HIV
87 test, were classified as *aware of HIV-positive status*. The specific laboratory algorithms
88 used to detect ARVs varied across surveys, although all were analyzed in the same

89 laboratory, and included drugs in the nationally recommended first- and second- line
90 regimens: efavirenz, lopinavir, and nevirapine (14-17).

91 **Bayesian latent class models**

92 Bayesian latent class models (18) were used to quantify the sensitivity of both self-
93 reported HIV testing history and HIV status awareness among PLHIV. Cross-tabulations
94 of self-reports with ARV biomarkers provide empirical information on their sensitivity
95 among those with detectable ARVs (Figure 1A).

96 With regard to participants with detectable ARVs, we assumed that: (1) they had been
97 tested for HIV, received their results, and were aware of their status; and (2) there were
98 no false positives in the detection of ARV metabolites, self-reported HIV testing history,
99 or awareness of HIV status.

100 As ARV metabolite data only provide information about the sensitivity of self-reports
101 among participants on ARVs, the ratio of non-disclosure for PLHIV without detectable
102 ARVs versus those with detectable ARVs was given a log-normal prior distribution with
103 a mean of $\log(1.48)$ (standard error: 4) to estimate the sensitivity of self-reports for
104 people without detectable ARVs. This prior was elicited by reviewing available studies
105 and meta-analyzing the evidence. The pooling of two studies conducted in rural
106 Mozambique and Malawi (19, 20) suggests that people not receiving ARVs are 1.48
107 more likely to not disclose their diagnosis. Additional analyses were conducted to
108 investigate the influence of this prior on our results. Equations and prior distributions are
109 presented in the *Supplementary Materials (Table S2 and Text S1)*.

110 Given known biases in self-reported estimates of HIV status awareness, analysts often
111 manually reclassify individuals not aware of their status but with detectable ARVs –as in
112 published PHIA reports. Most surveys, however, do not collect ARV biomarkers and
113 only rely on self-reported information. To examine the impact of this partial adjustment,
114 we compared the unadjusted, ARV-reclassified (as in PHIA reports), and Bayesian-
115 adjusted estimates of PLHIV aware.

116 Models were run separately for each country and for subgroup analyses (i.e. age, sex,
117 urban/rural and socio-economic status). Bayesian hierarchical models using Markov
118 Chain Monte Carlo (MCMC), implemented through the JAGS software (21) and the
119 *rjags* packages, were used to approximate the posterior densities (22, 23).

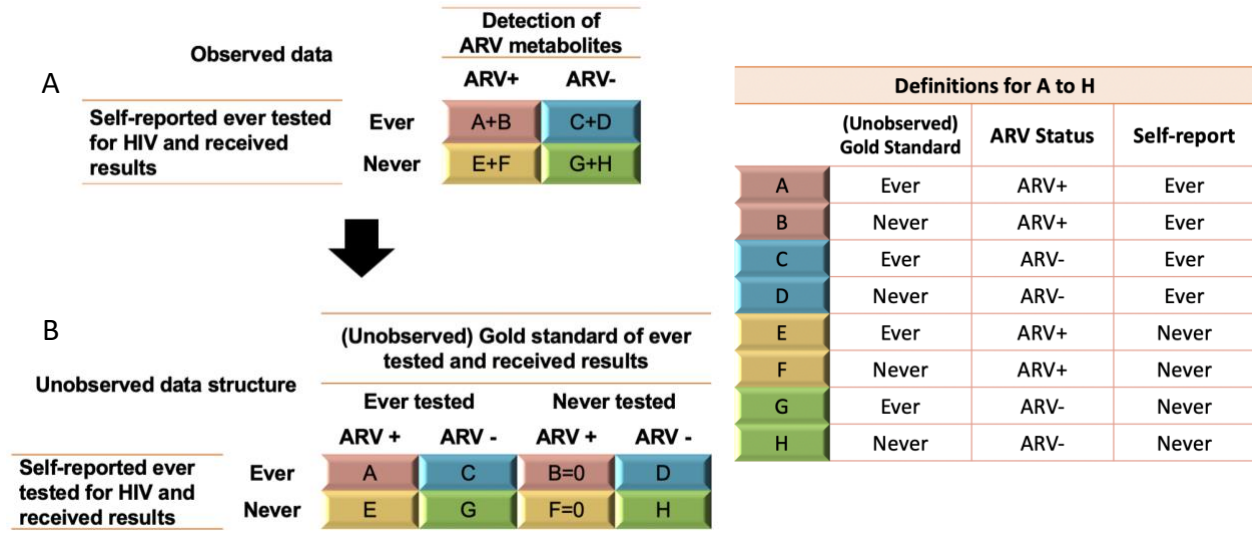
120 **Ethics**

121 Ethics approval for secondary data analyses was obtained from McGill University's
122 Faculty of Medicine Institutional Review Board (A10-E72-17B).

123

124

125



126

127 **Figure 1.** Observed and unobserved data structure of self-reported *ever tested and*
 128 *received results*, and antiretroviral (ARV) metabolites status. Definitions for cells A to H
 129 are listed in the table. As it was assumed that participants with detectable ARV must
 130 have been tested, cells B and F are *de facto* equal to zero. The same technique was
 131 applied to the self-reported awareness of HIV status and was applied to all four Sub-
 132 Saharan African countries.

133

134 **Results**

135 Overall, 3,003 PLHIV from Eswatini, 2,227 PLHIV from Malawi, 1,831 PLHIV from
136 Tanzania, and 2,467 PLHIV from Zambia were included in the analyses. In all countries,
137 a high fraction of PLHIV reported having ever been tested and the proportion of PLHIV
138 reporting being aware of their status ranged from 68.0% in Tanzania to 86.5% in
139 Eswatini. The proportion of PLHIV with detectable ARV metabolites was highest in
140 Eswatini (76.0%), followed by Malawi (68.1%), Zambia (61.5%), and Tanzania (53.9%).

141 **Sensitivity of self-report**

142 *Self-reported testing history*

143 Among participants with detectable ARVs, the estimated sensitivity was highest in
144 Eswatini at 99.5% (95% credible interval [95%CrI]: 99.2-99.8%), followed by Malawi
145 (98.2%; 97.5-98.8%), Zambia (97.4%; 96.5-98.1%), and Tanzania (96.6%; 95.3-97.6%)
146 (Figure 2). For people without ARV metabolites, the estimated sensitivity was 2.4%
147 points (0.1-11.4%) lower than those with detectable ARVs in Tanzania. The differences
148 were smaller elsewhere. Detailed values can be found in *Supplementary Table 3*.

149 *Self-reported awareness of HIV status*

150 The sensitivity of self-reported awareness of HIV-positive status among participants with
151 ARV metabolites was 97.4% (96.7-98.0%) in Eswatini, 94.2% (93.0-95.4%) in Malawi,
152 92.3% (90.5-93.8%) in Tanzania, and 91.6% (90.1-92.9%) in Zambia (Figure 2A). The
153 estimated differences in sensitivity between PLHIV with ARV metabolites and those

154 without were 1.8% points (0.1-8.5%), 4.2% points (0.2-19.6%), 5.7% points (0.3-26.7%)
155 and 6.2% points (0.3-29.0%) in Eswatini, Malawi, Tanzania, and Zambia respectively.

156 **Differences by gender, age, rural/urban, and socioeconomic status**

157 Among participants with detectable ARVs, women had 0.9-2.4% points higher
158 sensitivities of self-reported HIV testing history and HIV status awareness than men
159 (Figure 2B). The estimated sensitivities were the lowest at age 15-24 years (94.7-97.2%
160 for HIV testing history and 83.9-91.9% for HIV status awareness) in all of the countries
161 (Figure 2C). Participants residing in urban and rural areas had similar sensitivities
162 (Figure S1A) and variations by socio-economic status (SES) were also small (Figure
163 S1B and Figure S2).

164 **Adjusted proportion of PLHIV ever tested and PLHIV aware of their status**

165 Adjusting for imperfect sensitivity influenced the estimates of the self-reported
166 proportion ever tested for HIV less (largest difference between the adjusted and the
167 self-reports was 3.9% points in Tanzania) than the estimates of self-reported proportion
168 of PLHIV aware of their status (largest difference was 7.2% points in Zambia) (Figure
169 2D). Results were less affected by the assumed non-disclosure ratio for PLHIV without
170 detectable ARV metabolites when antiretroviral therapy (ART) coverage is high (Figure
171 S3).

172

It is made available under a [CC-BY 4.0 International license](https://creativecommons.org/licenses/by/4.0/).

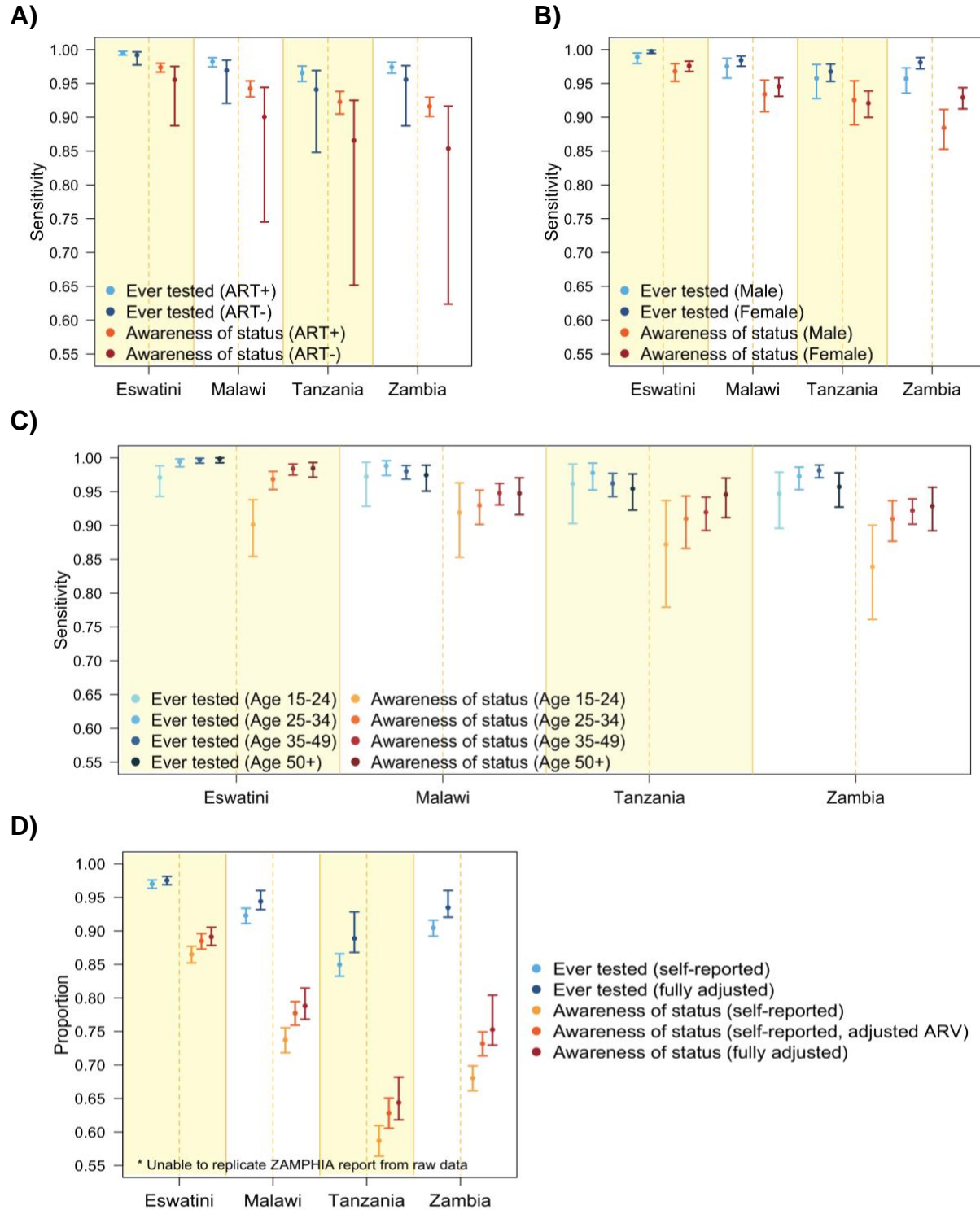


Figure 2. Marginal posterior medians and 95% credible intervals for selected outcomes. Sensitivity of self-reported ever tested and received results, and awareness of HIV-positive status among people living with HIV (PLHIV) by: (A) antiretroviral (ARV) metabolites status, (B) gender (ARV+), and (C) age groups (ARV+). Panel D portrays the overall proportion of PLHIV ever tested who received results and the awareness of HIV-positive status (self-reported vs. adjusted ARV metabolites status vs. fully adjusted).

174 **Discussion**

175 Self-reported information on HIV testing and diagnosis are primary data sources used to
176 monitor trends in the HIV treatment and care continuum (2, 9). These same data have
177 also been proposed to estimate cross-sectional HIV incidence (24). In this study, we
178 leveraged ARV biomarkers from four household representative surveys in Eswatini,
179 Malawi, Tanzania and Zambia to estimate the sensitivity of self-reported HIV testing
180 history and awareness of HIV status among PLHIV. We found that self-reports of HIV
181 testing history have a high sensitivity (>96%) among PLHIV with detectable ARVs
182 across these settings. Self-reported awareness of HIV status had a marginally lower
183 sensitivity (>91%) in these same countries.

184 Subgroup analyses revealed nonnegligible lower sensitivities of both self-reported HIV
185 testing history and awareness of status among male PLHIV and those aged 15-24 years
186 which could result from social desirability bias (25). Additionally, differences in survey
187 instruments could result in higher sensitivities for women. For example, in the PHIA
188 survey, women are asked about HIV testing up to 4 times (before pregnancy, during
189 pregnancy, during labor, and at their last HIV test), while men were asked only once. As
190 women were classified based on the positive response to any of the 4 questions, this
191 increased the probability of women disclosing their true status.

192 In this study, we estimated the sensitivity of the self-reports alone but when ARV
193 biomarkers are available, presentation of cascade results from the surveys usually
194 adjust these self-reports by reclassifying PLHIV that do not disclose their status but for
195 which ARV metabolites are detected as “aware”. We have found that this partial

196 adjustment may be insufficient, especially if ART coverage is low in the surveyed
197 population and the ratio of non-disclosure among those not on ART is high (26-29). To
198 accurately estimate awareness of status, results must also be adjusted for non-
199 disclosure among PLHIV with undetectable ARVs.

200 Our results need to be interpreted considering certain study limitations. First, only four
201 PHIA surveys have publicly available micro-data, none of which are located in the West
202 and Central African regions, where non-disclosure could be higher (30). The PHIA
203 included here had some of the lowest levels of non-disclosure of these reviewed studies
204 suggesting that other settings could have lower sensitivities. Second, our study design
205 limited our assessment of the sensitivity of testing history to PLHIV, and findings should
206 not be extrapolated to people not living with HIV. Third, it is not possible to empirically
207 validate the sensitivity of self-reports among PLHIV without ARV metabolites. As such,
208 we had to use information from two previous studies that used medical records to inform
209 the non-disclosure ratio. Results could be sensitive to this non-disclosure ratio but the
210 high ART coverage in the four countries mitigates this influence (*Figure S3*). Finally, the
211 specificity of self-reports was assumed to be 100% which could lead to overestimating
212 the proportion of PLHIV ever tested / aware of HIV-positive status. However, previous
213 study has shown a high specificity of self-reported HIV testing results (11) implying that
214 this assumption will likely have little impact on the outcomes.

215 Strengths of this study include the use of standardized survey and laboratory data (i.e.
216 detection of ARV metabolites). Second, the Bayesian latent class models propagate
217 uncertainty to our results by assuming prior distributions and generating posterior

218 credible intervals. Finally, we examined sex, age, urban/rural, and SES differences in
219 the sensitivity of self-reports.

220 In conclusion, self-reported HIV testing histories have high sensitivities in the four
221 countries examined but self-reported awareness of HIV status are lower. Whenever
222 available, ARV biomarkers data can be used to adjust self-reports but such adjustments
223 may still underestimate diagnosis coverage, especially if ART coverage is low in that
224 population. Future research should extend this work in other regions and populations.

225 **Acknowledgements**

226 We acknowledge funding from the *Steinberg Fund for Interdisciplinary Global Health*
227 *Research* (McGill University). MMG's research program is funded through a *Canada*
228 *Research Chair* (Tier 2) in *Population Health Modeling*. JWE acknowledges funding
229 from the Bill and Melinda Gates Foundation and UNAIDS. MCB acknowledge funding
230 from MRC Centre for Global Infectious Disease Analysis (MRC GIDA, MR/R015600/1).
231 This award is jointly funded by the UK Medical Research Council (MRC) and the UK
232 Department for International Development (DFID) under the MRC/DFID Concordat
233 agreement and is also part of the EDCTP2 programme supported by the European
234 Union. LJ acknowledges funding from UNAIDS.

235

236 REFERENCES

- 237 1. UNAIDS. 90 – 90 – 90: an ambitious treatment target to help end the AIDS epidemic.
238 Geneva: Joint United Nations Programme on HIV/AIDS (UNAIDS); 2014.
- 239 2. Rentsch CT, Georges Reniers, Richard Machemba, Emma Slaymaker, Milly Marston,
240 Alison Wringe, et al. Non-disclosure of HIV testing history in population-based surveys:
241 implications for estimating a UNAIDS 90-90-90 target. *Global Health Action*.
242 2018;11(1):1553470.
- 243 3. UNAIDS. UNAIDS data 2019.
- 244 4. Sarah Staveteig SW, Sara K. Head, Sarah E.K. Bradley, Erica Nybro. Demographic patterns
245 of HIV testing uptake in sub-Saharan Africa: DHS comparative reports 30. Calverton: ICF Macro;
246 2013.
- 247 5. Kim AA, Mukui I, Young PW, Mirjahangir J, Mwanyumba S, Wamicwe J, et al.
248 Undisclosed HIV infection and antiretroviral therapy use in the Kenya AIDS indicator survey
249 2012: relevance to national targets for HIV diagnosis and treatment. *AIDS*. 2016;30(17):2685-
250 95.
- 251 6. Anand A, Shiraishi RW, Bunnell RE, Jacobs K, Solehdin N, Abdul-Quader AS, et al.
252 Knowledge of HIV status, sexual risk behaviors and contraceptive need among people living
253 with HIV in Kenya and Malawi. *AIDS*. 2009;23(12):1565-73.
- 254 7. Cherutich P, Kaiser R, Galbraith J, Williamson J, Shiraishi RW, Ngare C, et al. Lack of
255 knowledge of HIV status a major barrier to HIV prevention, care and treatment efforts in Kenya:
256 results from a nationally representative study. *PLoS One*. 2012;7(5):e36797.
- 257 8. Maheu-Giroux M, Marsh K, Doyle CM, Godin A, Laniece Delaunay C, Johnson LF, et al.
258 National HIV testing and diagnosis coverage in sub-Saharan Africa: a new modeling tool for
259 estimating the 'first 90' from program and survey data. *AIDS*. 2019;33 Suppl 3:S255-S69.
- 260 9. Organization WH. Consolidated strategic information guidelines for HIV in the health
261 sector. Geneva: World Health Organization; 2015.
- 262 10. Fishel JD BB, Kishor S. Validity of data on self-reported HIV status and implications for
263 measurement of ARV coverage in Malawi. DHS Working Paper No. 81. Calverton, Maryland,
264 USA: ICF International; 2012.
- 265 11. Fisher DG, Reynolds GL, Jaffe A, Johnson ME. Reliability, sensitivity and specificity of self-
266 report of HIV test results. *AIDS Care*. 2007;19(5):692-6.
- 267 12. Rohr JK, Xavier Gomez-Olive F, Rosenberg M, Manne-Goehler J, Geldsetzer P, Wagner
268 RG, et al. Performance of self-reported HIV status in determining true HIV status among older
269 adults in rural South Africa: a validation study. *J Int AIDS Soc*. 2017;20(1):21691.
- 270 13. Goncalves L, Subtil A, de Oliveira MR, do Rosario V, Lee PW, Shaio MF. Bayesian Latent
271 Class Models in malaria diagnosis. *PLoS One*. 2012;7(7):e40633.
- 272 14. Malawi population-based HIV impact assessment (MPHIA) 2015-2016 data use manual
273 supplement. New York, NY; December 2018.
- 274 15. Swaziland HIV incidence measurement survey 2 (SHIMS2) 2016-2017 data use manual
275 supplement. New York, NY; April 2019.
- 276 16. Tanzania HIV impact survey (THIS) 2016-2017 data use manual supplement. New York,
277 NY; December 2018.

- 278 17. Zambia population-based HIV impact assessment (ZAMPHIA) 2016-2017 data use
279 manual supplement. New York, NY; February 2019.
- 280 18. Joseph L, Gyorkos TW, Coupal L. Bayesian estimation of disease prevalence and the
281 parameters of diagnostic tests in the absence of a gold standard. *Am J Epidemiol*.
282 1995;141(3):263-72.
- 283 19. Fuente-Soro L, Lopez-Varela E, Augusto O, Saco C, Nhacolo A, Honwana N, et al.
284 Monitoring progress towards the first UNAIDS target: understanding the impact of people living
285 with HIV who re-test during HIV-testing campaigns in rural Mozambique. *J Int AIDS Soc*.
286 2018;21(4):e25095.
- 287 20. Chasimpha SJD, McLean EM, Dube A, McCormack V, Dos-Santos-Silva I, Glynn JR.
288 Assessing the validity of and factors that influence accurate self-reporting of HIV status after
289 testing: a population-based study. *AIDS*. 2020;34(6):931-41.
- 290 21. Plummer M, editor JAGS: A Program for Analysis of Bayesian Graphical Models Using
291 Gibbs Sampling. Proceedings of the 3rd International Workshop on Distributed Statistical
292 Computing (DSC 2003); 2003 March 20–22; Vienna, Austria.
- 293 22. Alan E. Gelfand AFMS. Sampling-based approaches to calculating marginal densities.
294 *Journal of the American Statistical Association*. 1990;85(410):398-409.
- 295 23. Alan E. Gelfand SEH, Amy Racine-Poon, Adrian F. M. Smith. Illustration of Bayesian
296 inference in normal data models using Gibbs sampling. *Journal of the American Statistical*
297 *Association*. 1990;85(412):972-85.
- 298 24. Fellows IE, Shiraishi RW, Cherutich P, Achia T, Young PW, Kim AA. A new method for
299 estimating HIV incidence from a single cross-sectional survey. *PLoS One*. 2020;15(8):e0237221.
- 300 25. Mooney AC, Campbell CK, Ratlhagana MJ, Grignon JS, Mazibuko S, Agnew E, et al.
301 Beyond social desirability bias: investigating inconsistencies in self-reported HIV testing and
302 treatment behaviors among HIV-positive adults in North West province, South Africa. *AIDS*
303 *Behav*. 2018;22(7):2368-79.
- 304 26. Eswatini GotKo. Swaziland HIV incidence measurement survey 2 (SHIMS2) 2016-2017.
305 Final report. Mbabane: Government of the Kingdom of Eswatini; April 2019.
- 306 27. Ministry of Health M. Malawi population-based HIV impact assessment (MPHIA) 2015-
307 2016: Final report. Lilongwe: Ministry of Health; October 2018.
- 308 28. Tanzania Commission for AIDS (TACAIDS), (ZAC) ZAC. Tanzania HIV impact survey (THIS)
309 2016-2017: Final report. Dar es Salaam: Tanzania; December 2018.
- 310 29. Ministry of Health Z. Zambia population-based HIV impact assessment (ZAMPHIA) 2016:
311 Final report. Lusaka: Ministry of Health; February 2019.
- 312 30. Eba PM. HIV-specific legislation in sub-Saharan Africa: A comprehensive human rights
313 analysis. *African Human Rights Law Journal*. 2015;15:224-62.
- 314