Psychology & Health

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gpsh20

A longitudinal multilevel analysis of the evermigrated population subjective HIV infection expectation in Malawi

Sally Sonia Simmons

To cite this article: Sally Sonia Simmons (2022) A longitudinal multilevel analysis of the evermigrated population subjective HIV infection expectation in Malawi, Psychology & Health, 37:7, 890-902, DOI: 10.1080/08870446.2021.1910697

To link to this article: https://doi.org/10.1080/08870446.2021.1910697

Published online: 20 Apr 2021.

PSYCHOLOGY & HEALTH
2022, VOL. 37, NO. 7, 890–902
https://doi.org/10.1080/08870446.2021.1910697

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

A longitudinal multilevel analysis of the ever migrated population subjective HIV infection expectation in Malawi

Sally Sonia Simmons[a,b]

[a]Department of Social Policy, London School of Economics and Political Science, London, UK; [b]Institute of Demography, National Research University-Higher School of Economics, Moscow, Russia

ABSTRACT

Objective: The primary purpose of this study is to assess the variance in the effects of factors influencing ever migrated Malawian population's subjective HIV infection expectation.

Design: Using data from the Malawi Longitudinal Study of Families and Health (MLSFH) survey (1998-2010), 7805 ever migrated Malawian adults were selected for the study. Summary statistics, logistic regression and longitudinal multi-level models were fitted for the study. A binary logistic regression was used to estimate the direction and magnitude of the associations between the variables selected for the study Five multilevel models with random intercepts and coefficients nominal response were fitted.

Results: The study revealed that sexual behaviours had the most significant effect on ever migrated Malawian's subjective HIV infection expectation. All metrics showed that the conditional growth model had the most signficant outcome. The addition of time and other variables as predictors had a significant effect on the conditional growth model.

Conclusion: Interventions designed to decrease the spread of HIV should target sexual behaviours and widespread testing among the ever migrated population to reduce subjective HIV infection thoughts.

ARTICLE HISTORY
Received 13 May 2020
Accepted 22 March 2021

KEYWORDS
HIV; subjective; expectation; ever migrated; population; Malawi

Introduction

The relationship between mobility and Human Immunodeficiency Virus (HIV) has been long accepted as scholarly evidence shows that migration drives the spread of HIV (McGrath et al., 2015; Ross et al., 2018). The epidemiology, however, varies across the globe given the fact that population movements and HIV have vitiated countries in sub-Saharan Africa (SSA) than other regions of world (P. Anglewicz et al., 2016; McGrath et al., 2015). In SSA, specific population groups such as the ever migrated population have contributed to the spread of the virus (P. Anglewicz, 2012). Consequently, the ever migrated population are at a higher risk of HIV infection than non-migrants in this region of the world (P. Anglewicz et al., 2016; McGrath et al., 2015). Pro social ecology

CONTACT Sally Sonia Simmons ssimmons@edu.hse.ru Department of Social Policy, London School of Economics and Political Science, London, UK.

scholars argue that the nature of the current epidemiology is influenced by multiple and interrelated factors (e.g; behaviour, demographics, social, economic that operate at different levels (Golden & Earp, 2012; Mayer et al., 2008; Weine & Kashuba, 2012).

Malawi has one of the highest HIV prevalence rates (~9.2%) among adults (Nutor et al., 2020) in SSA. In 2012, for instance, about 11% of the Malawian population were infected with HIV. There are regional differences in the distribution of HIV in Malawi, with the areas in the North, Central and South having the highest, higher and lowest rates, respectively (Geubbels & Bowie, 2006; Poulin & Muula, 2011; Wirth et al., 2017). Several HIV prevention and control programmes, including antibody testing, have been implemented in Malawi. However, the preference for HIV antibody test is dependent on an individual's health status thoughts and perceived HIV infection risk (Simmons, 2019). Further, the perceived susceptibility of HIV can be affected by mobility and its associated activities (Colebunders & Kenyon, 2015; McGrath et al., 2015). Malawian men who have ever migrated have 4% higher HIV infection rate than non-migrant male Malawians (Dobra et al., 2017; Feldacker et al., 2010). Common scholarly interpretation is that persons who have ever migrated frequently separate from their families and spouses, disconnect from their known sexual network, and adapt to new customs and cultures. When destination areas have higher HIV prevalence than origin communities, these migrants have an increased risk of HIV acquisition (McGrath et al., 2015). Also, such persons are likely to experience sexual violence (P. Anglewicz et al., 2018) which may contribute to increased HIV risk.

Researchers studying the relationship between migration and HIV in Malawi have found that changes in behaviours among migrants influence perceived risk of contracting the disease (P. Anglewicz, 2012; P. Anglewicz et al., 2016; Dobra et al., 2017). However, there are uncertainties regarding whether an ever-migrated individual's perceived risk of contracting HIV correlate with other determinants over time or not. No longitudinal studies has been conducted to clearly describe the different factors influencing the subjective HIV infection expectation of the ever migrated population in the country. The basis of this study is, therefore, modelling the variance in the effects of factors influencing ever migrated population's subjective HIV infection expectation using fixed and random intercepts and coefficients nominal response models. The variance in the effects represents the presence or absence of subjective HIV infection expectation. Thus, by considering changes over time, the study will compare three approaches of the generalised multilevel nominal models; namely the unconditional mean, unconditional growth and conditional growth models. Such knowledge is of critical importance in the practical design and implementation of HIV intervention programs in Malawi.

Methodology

Data

The Malawi Longitudinal Study of Families and Health (MLSFH) survey (1998–2010) is the source of data for the study. From 1998 to 2010, the MLSFH survey investigated the varying degrees of HIV and other Sexually Transmitted Infection (STI) risks in three regions of Malawi, namely; central, southern and northern regions. Over time, the initial scope was broadened to include other essential measures. A detailed description of the MLSFH survey, including, data and data collection process are provided on the project website and in Kohler et al. (2015).

Data analysis

The study used the MLSFH survey data from 1998, 2001, 2008 and 2010. The third wave of the survey was omitted from the study because some variables of interest were excluded. A total of 12,750 samples was extracted as a repeated sample generated from the four study periods indicated above. Within the sample, 21 variables were selected from four domains of variables: migration; socio-demographic; sexual behaviour; health. These were respondent ID, worried about infection, sexual partners 12 months, infidelity, infection expectation, current health to previous health, marital status, level of education, contraception (condom use), ever migrated, travelled to Lilongwe, travelled to Blantyre, travelled to Mzuzu, travelled to Zomba, number of sexual partners, safer sex (condom use with partner), sex, time (study period), year of birth, age. These variables were adapted from the dataset to best suit the analytical method of the study (Jovic et al., 2015). In addition, the raking ratio estimation method was applied to age and sex to create weights for the study (Dal Grande et al., 2015). Except for the outcome variable, infection expectation, none was coded as a binary variable. While missing ages were estimated from the year of birth provided, the frequency of all other missing data were computed to understand the pattern of missingness (Soley-Bori, 2013). About 15 to 30% of data were missing but missing data for the variables were found to be conditional on other variables (missing at random) (Schafer, 1999). The missing values were replaced by multiple ordered monotone blocks values ('multiple imputed values'). The pattern of missing data was decomposed into clusters of constructed monotone patterns. A sequential strategy was used to impute the missing values in each cluster to account for uncertainty about the imputed values and increase compatibility among univariate conditional distributions (Li et al., 2014). The ever migrated population was limited to all participants who responded with a 'yes' to the question 'Have you travelled to other towns or cities in Malawi?' to achieve a more efficient analytical outcome (Jovic et al., 2015). In effect, the final sample for the study was 7,805.

The distribution of HIV infection expectation among the ever migrated population over time and space was integrated into the study. Internal migration variables labelled as travelled to Mzuzu, Blantyre, Lilongwe and Zomba were used for this purpose. This step was introduced to provide a clearer understanding of regional variations in subjective HIV infection among ever migrated population in Malawi (Vetter, 2017). A weighted distribution of the reported subjective HIV infection was presented.

A binary logistic regression model was fitted to estimate the direction and magnitude of the associations between the variables to be used for the multi-level modelling. This technique helped to assess the potential variance in the response variable (infection expectation) and identify the variables that could be used to generate a parsimonious model (Talenti et al., 2015). For this regression model, the initial interaction, each sub-interactions and the main effects were estimated for equality of means. The variables with significant effects, eight out of 12, were included in the next model. These variables became sex, age, infidelity, marital status, worried about infection, number of sexual partners, level of education and safer sex (condom use with partner).

In the third phase of the study, multi-level models were fitted. These models accounted for all incomplete cases in longitudinal studies, where levels of attrition can be high (Jin et al., 2015; Steele, 2008). Two-level models for change were developed to investigate the relationship between time and how subjective HIV infection varies among Malawians as a function of selected person-level variables. At level one (1), fitted models measured how much an ever migrated Malawian's subjective thought of HIV infection varied occasionally (each period under study) (Bell et al., 2019). The mean of the change for subjective HIV infection thought for an ever migrated Malawian was assessed to describe the within-person variation in subjective HIV infection thought in Malawi (Curran & Bauer, 2011). At level two (2), fitted models measured how much subjective thought of HIV infection varied between ever migrated Malawian. It described the between-person variation in average subjective thought of HIV infection for the whole period under study as a function of the grand mean for all ever migrated Malawians, and the difference between the grand mean and ever migrated Malawian's mean for all years (Bell et al., 2019; Hoffman & Stawski, 2009). Thus, contexts have been defined as persons by explicitly modelling differences in person mean in subjective thought of HIV infection in Malawi (Hoffman & Stawski, 2009). A base model was introduced to assist with the estimation of between- and within-individual variance and to serve as a benchmark for comparison between subsequent longitudinal models (Holden et al., 2008; Tasca et al., 2009). The base model, unconditional means model (UMM), had no time factor and therefore functioned not as a longitudinal model. The UMM used a maximum likelihood estimation method because it has relatively accurate frequentist properties as compared to other methods of estimation (Oliveira & Ferreira, 2011). Below is a representation of this model;

$$Level\,1: y_{ij} = \pi_{oij} + \varepsilon_{ij}$$

$$Level\,2: \pi_{oij} = \beta_{ooj} + r_{oij} \tag{1}$$

where, at level 1, y_{ij} is the dependent variable score (infection expectation) for the repeatedly measure for i_{th} individual $(i = 1, \ldots, N)$ nested within group j, π_{oij} is the intercept for the i_{th} individual or the individual mean score for every time points, ε_{tij} is the error in predicting the i_{th} individual score from their overall mean score. At level 2, β_{ooj} is the intercept of the intercept at level1 and it is modelled as a group mean of each individual score. r_{1ij} is the unique effect of the i_{th} individual on the intercept. The intra-class correlation coefficient (ICC) was estimated to check for potential clustering in the data. The outcome of the ICC estimate informed the development of the unconditional growth and conditional growth models. The unconditional growth model (UGM) unlike the UMM included "time" as a predictor and thus, setting up the slopes, fixed and random gradients, to assess the individual similarity or variability progression in the phenomenon of interest. The mathematical representation of the UGM model is indicated below;

$$Level\,1: y_{tij} = \pi_{otij} + \pi_{1tij}(time) + \varepsilon_{tij}$$

$$Level\ 2: \pi_{oij} = \beta_{ooj} + r_{oij}$$

$$\pi_{1tij} = \beta_{1oj} + r_{1ij} \tag{2}$$

where the rate of change or within-person growth is modelled at level 1 and π_{ntij}, is the initial status for the i_{th} individual $(i = 1,\ldots,N)$ during a given period, the time metric (1998, 2001, 2008 and 2010). $\pi_{1tij}(time)$ represents the slope of the model and defines the growth rate for the i_{th} for every year whereas ε_{tij}, is the error term showing the deviation of each i_{th} 's score from his or her own modelled line. The rate of change or between-person growth variability is modelled at level 2. Here, the π_{ntij}, intercept for the i_{th} individual or the individual mean score for every time points, represents β_{ooj}, a function of the group mean of the i_{th} individual score and r_{1ij}, the residual. The rate of change over time, π_{ntij}, represents the mean rate of change for the i_{th} individual's group (β_{ooj}), the connections between the individual group centred score and the i_{th} individual's growth parameters' deviation from the mean rate of change, r_{1ij}. Next, was the introduction of the full model, conditional growth model, to answer the main research question. It contained a fixed effect and random slope and was modelled as;

$$Level\ 1: y_{tij} = \pi_{otij} + \pi_{1tij}(time) + \pi_{2tij}(X_{itj}) + \ldots + \pi_{ntij}(X_{nitj}) + \varepsilon_{tij}$$

$$Level\ 2: \pi_{oij} = \beta_{ooj} + \beta_{o1j}(X_{itj}) + \ldots + (X_{nitj}) + r_{oij}$$

$$\pi_{1tij} = \beta_{1oj} + \beta_{11j}(X_{itj}) + \ldots + (X_{nitj}) + r_{1ij} \tag{3}$$

At level 1, $\pi_{2tij} \ldots \pi_{ntij}$ were the regression weights for predictors, $(X_{itj})\ldots(X_{nitj})$. At level 2, β_{o1j} represents that the individual's group centred score and β_{11j} is each individual's growth parameters' deviation from the mean rate of change. A chi-square test was undertaken to assess whether there will be a variance remaining to be accounted for the predictors, the variance component were examined from the growth models. All models in the study were weighted to adjust for population size effect and computed using R progamme.

Results

Figure 1 shows the distribution of ever migrated population HIV infection expectation in Malawi over space and time. The prevalence of HIV infection expectation were not in unison across space and time. Malawians who had travelled to Lilongwe recorded the highest expected HIV infection, whereas those who went to Zomba were the least expectant. Initially, persons whose destination was Blantyre recorded the second-highest expected, but in the final year, these travellers were replaced by those from Mzuzu.

Table 1 shows the outcome of the binary logistic regression analysis. All variables but ever use a condom, sexual partners in the last 12 months and the polynomial

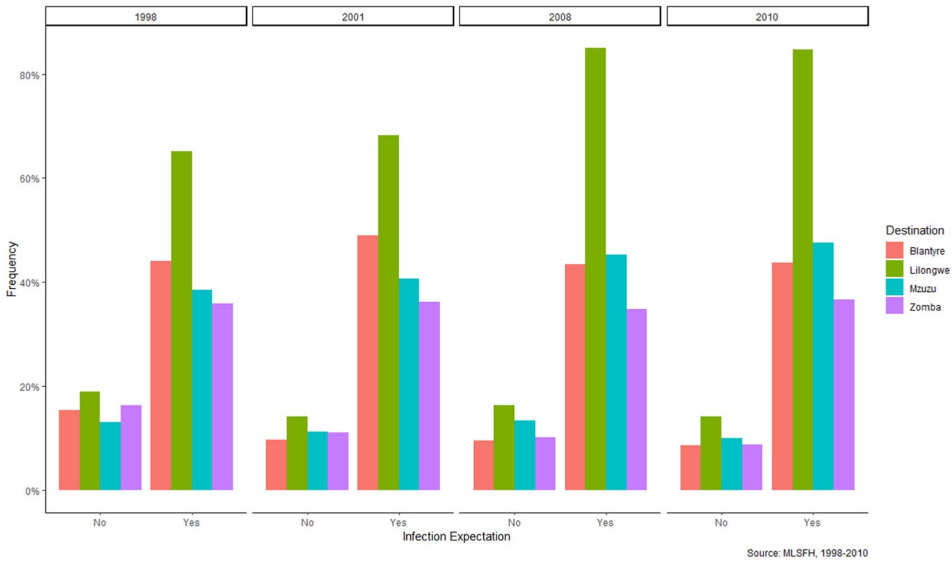

Figure1. Subjective HIV infection expectation across destinations in Malawi.

Table 1. Results of the logistic regression model for feature selection.

Predictors	Coef	SE & p-value
Demographic		
Age	−0.01	(0.01)**
Sex	−0.18	(0.07)**
Marital status	0.16	(0.05)***
Education	−0.16	(0.07)*
Sexual behaviour and health		
Number of sexual partners	0.07	(0.02)***
Infidelity	0.12	(0.03)***
Current to previous health	−0.10	(0.04)**
Ever use condom	−0.15	(0.09)
Safer sex (condom use with partner)	−0.16	(0.08)*
Sexual partners in the last 12 months	0.05	(0.03)
Worried about infection	1.12	(0.04)***
Transformations		
Age^2	0.00	(0.03)
Sex & Age^2	−0.05	(0.02)**
Fit statistics		
AIC	7243.8	
Constant	4.56	(0.21)***

Source: MLSH, 1998–2010.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$, standard errors (SE) appear in parentheses, coef: coefficient.

function of age had a statistically significant relationship with subjective infection. It was revealed that an ever migrated Malawian was less likely to have the thoughts of HIV infection with age, sex, education, improved health, safer sex practices or was an older female. Also, these Malawians were more likely to have the thoughts of HIV infection if they were not in a marital union, had multiple sexual partners, practiced adultery, frequently worried about the possibility of being infected.

Table 2. Results of the multilevel models.

Parameter	Model				
	1	2	3	4	5
Fixed effects					
Constant	0.72***(0.01)	0.74***(0.03)	0.74***(0.03)	1.23***(0.04)	1.05***(0.06)
Time		0.01***(0.00)	0.03***(0.00)	0.01** (0.00)	0.04***(0.04)
Age				−0.13** (0.01)	−0.03***(0.03)
Sex				−0.01* (0.01)	−0.02* (0.02)
Marital status				0.03***(0.02)	0.03***(0.01)
Education				−0.06* (0.04)	−0.04* (0.09)
Number of sexual partners				0.18***(0.03)	0.15***(0.05)
Infidelity				0.17** (0.05)	0.16** (0.04)
Current to previous health				−0.09***(0.01)	−0.02***(0.00)
Condom use with partner				−0.14***(0.09)	−0.09***(0.07)
Worried about infection				0.13***(0.05)	0.14***(0.04)
Sex & Age^2					−0.02** (0.06)
Random effects					
σ_{ε}^2	5.86	5.85	4.58	1.90	1.89
σ_{r0}^2	3.64	4.09	1.99	6.31	6.12
σ_{r1}^2		0.17	0.17	0.17	0.17
τ_{o1}		−0.21	−0.22	−0.24	−0.22
Fit statistics					
Deviance	7334.6	7323.0	7301.5	7236.7	7236.2
AIC	7360.6	7341.0	7332.5	7311.7	7311.2
BIC	7391.0	7368.2	7353.4	7347.0	7351.3
Loglik	−3662.3	−3646.5	−3640.3	−3141.9	−3138.1
Model comparisons					
		$\chi_{12}^2 = 11.60$***	$\chi_{13}^2 = 33.10$***	$\chi_{14}^2 = 97.90$***	$\chi_{15}^2 = 98.40$***
			$\chi_{23}^2 = 21.50$***	$\chi_{24}^2 = 86.30$***	$\chi_{25}^2 = 86.80$***
				$\chi_{34}^2 = 64.80$***	$\chi_{35}^2 = 65.30$***
					$\chi_{45}^2 = 0.50$
ICC	0.32	0.41	0.69	0.77	0.77
Pseudo R^2 (level 1)					
		$R_{12}^2 = 0.24$	$R_{13}^2 = 0.24$	$R_{14}^2 = 0.24$	$R_{15}^2 = 0.24$

Source: MLSH, 1998–2010.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$, standard errors (SE) appear in parentheses, fixed effects estimates are reported before the p-values. Variance components: σ_{ε}^2 population error variance (residual variance) of the base model, σ_{r0}^2 & σ_{r1}^2: variance of unique effects, τ_{o1}: covariance of person (intercept) time. AIC: Akaike Information Criterion (AIC), BIC: Bayesian Information Criterion, Loglik: Log-likelihood, ICC: Intra-Class Correlation Coefficient, X^2: Chi-square test outcome between models.

Table 2 compares the results of the five nested data models. It captures the outcome of the fixed and random effects, analysis of the fit statistics; the AIC, log likelihood, deviances, BIC and χ^2, the intra-class correlation and pseudo R^2. Generally, the growth models (2 to 5) showed that effect of time was statistically significant from zero, indicating that HIV infection expectation increased for per period, from 1998 to 2010, and the increase was maintained for the 12 years. All the metrics are in agreement that model 4 provides the best fit to the data as all predictors yielded a statistically significant effect. On the average, ever migrated Malawians who were older were had lower [1.10 (ie; 1.23-0.13, $p < 0.01$)] subjective HIV infection thoughts than those who were younger [1.23(β_{00} , $p < 0.001$)]. Similarly, ever migrated Malawians who practiced safer sex likewise those who were currently healthier than in previous years had lower [(1.09 (ie; 1.23-0.14, $p < 0.001$), 1.14 (ie; 1.23-0.09, $p < 0.001$)], respectively) HIV infection expectations than those who avoided safer sex [1.23(β_{00} , $p < 0.001$]) and had poor health experiences [1.23(β_{00} , $p < 0.001$)]. There is a relatively weak negative correlation estimated between initial status and rate of change (τ =-0.2) indicating that the ever migrated population who had expected HIV tend to experience less change over time due to the predictors than do individuals who begin with no expectation of being infected with HIV.

Discussion

The study investigated subjective HIV expectation among ever migrated Malawians. Specific factors were incorporated to determine the subjectivity of the ever migrated Malawian population HIV infection expectation. Generally, the ever migrated Malawian expectations of being infected with HIV is neither evenly distributed in the country nor independent of other correlates of HIV.

It was observed that the distribution of expected HIV infection if an ever migrated Malawian had travelled to specific areas in the country had a spatio-temporal variation. Similar findings have been reported by studies conducted in Malawi, where certain areas and regions in the country had a higher prevalence of HIV infection (P. Anglewicz et al., 2016; Geubbels & Bowie, 2006; Poulin & Muula, 2011; Wirth et al., 2017). The observed spatial disparity can be explained by individual and place factors. Urban areas like Lilongwe have a higher prevalence of HIV. Such areas are popular migrant destinations (Feldacker et al., 2010; McGrath et al., 2015; Nutor et al., 2020). Thus, engagement in risky sexual behaviours while settling in such cities increases vulnerability to HIV infection. Moreover, the spread of the epidemic from one city to other might have had influenced the perceived infection status of Malawians who had travelled to destinations where HIV infection was formerly regarded as less endemic. These findings indicate a need for more effective HIV intervention programmes to improve awareness, testing management and control among Malawians.

An ever migrated Malawian's level of subjective HIV expectations varies with sexual behaviours and observables characteristics like age, sex. Sexual behaviours, in particular, accounted for an increased expectation of HIV infection over time. It could be the result of relentless thoughts of the possible effects of continuous engagement in risky sexual activities which could have also been behaviours formed at the same time as migrants since risky sexual behaviours, in the form of concurrent long-term sexual relationships and unprotected sex, have been identified as frequent facilitators of the spread of the infection among migrant populations (P. Anglewicz et al., 2016; Dobra et al., 2017). In addition, infidelity was found to increase subjective infection expectations among ever migrated Malawians. This finding confirms P. A. Anglewicz et al. (2010) argument that perceived HIV infection is closely related to spousal sexual behaviour. An ever-migrated Malawian's perceived HIV infection is intertwined with his or her spouse's faithfulness. A reason is that extramarital relationships are well known to be drivers of the spread of HIV in Malawi. Research has revealed that concurrent long-term sexual relationships unlike monogamy in the dynamics of sexual networks rapidly spreads HIV. Again, anthropologist have emphasised the role of social structure in legitimising such relationships for males in particular (Djamba, 1997). Such relationships are often companied by unprotected sex (irregular condom use). Unprotected sex increases the capacity to be infected and infect one's spouse is high. Second, many ever-migrated Malawians are knowledgeable about their actual HIV status, effects of infidelity and unprotected sex. Thus they are likely to judge their HIV risk subjectively because of the known consequence of infidelity (P. A. Anglewicz et al., 2010).

Similar to Du et al. (2015) research findings, it was observed that ageing and sex accounted for a decrease in the expectancy of subjective HIV infection among the ever migrated Malawians. Older females, unlike their younger counterparts, are less promiscuous as prevalence of sexual dysfunction is common among older females and even relatively higher in the postmenopausal years. Older female cohorts are less likely to engage in regular risky sexual activities, a leading factors for the spread of HIV. The irregularity, which might be due to death of a spouse, poor physical and mental health and break down of communication (Ambler et al., 2012), has the potency to decrease the thoughts of HIV infection. Another aspect to consider is the reason for becoming an ever migrated Malawian. Females who were once migrants migrated mostly because of marriage, family reunion or higher education (Fleury, 2016). More often than not, women including those who had ever migrated remain in serial monogamy when they are married. Also, these females tend to believe their partners do same and therefore fail to think about probable HIV infection because of the perceived non-existence of infidelity (Muhwava, 2004).

In contrast, males had a higher HIV infection expectations and reasons for this are opened to speculation. It could be that older males have frequently engaged risky sexual activities in the past and had few or no HIV test outcomes because of fear and HIV related stigma. Their unknown status increases their infection expectations because they are likely perceive themselves susceptible to HIV (Mandiwa & Namondwe, 2019). Differently, older unlike younger Malawians had lower subjective expectation of HIV infection. Elsewhere, this perception has been attributed to the finding that older people are more likely to be tested for HIV and become aware of their HIV status (Peltzer & Matseke, 2013). The higher uptake of HIV test could be due to access to such services, HIV related knowledge and the need to reduce infection status anxiety (P. Anglewicz et al., 2016; Mandiwa & Namondwe, 2019). Sex and ageing differences, combined with other factors, suggest that programme planners need to develop and design age and sex-specific interventions that target ever migrated males and females within specific age groups separately in Malawi.

Person-level variance can be interpreted as heterogeneity across the ever migrated for the probability of having subjective HIV infection expectations. The observed random effects are outcomes of the sexual behaviour and demographic characteristics influencing subjective HIV infection expectations. The interactions between these determinants across all years are responsible for the outcome variability. Hence, the addition of time and other variables as predictors to the intercept had a significant effect on the model. All the metrics were in agreement that model 4 provided the best fit to the data.

Practical implications

As the burden of HIV lingers in SSA, the findings of the study offer considerations for researchers and practitioners who seek to address HIV risk among Malawians with potential subjective HIV expectations. To clarify the relationship between personal feelings and HIV among the ever-migrated population in Malawi, these findings suggest the need for further studies. Comprehensive qualitative and quantitative studies are needed to describe subjective HIV infection among Malawians with circular migration patterns and how behavioural, social, and situational risk factors present at place of origins and destinations to which ever-migrated Malawians are exposed affect subjective HIV infection. The research will inform how HIV treatment and prevention programmes resources may be redistributed especially at transmission hotspots.

The study has some limitations. First, the reduction of predictors to a specific class of variables is a limitation. This was due to the need for the creation of a parsimonious model. Second, because of the convenient nature of the sample of destination zones (four instead of 28 cities) for the internal migrants, it is evident the distribution of subjective HIV expectation from other areas in Malawi was not discussed. Thus, the omission of 24 cities constitutes a severe limitation but the four areas included in the study are the main destination zones for internal migrants in the country. The study, however, presents valuable findings for future analysis of HIV infection expectation among the ever migrated Malawian population.

Conclusion

In summary, the study has demonstrated a significant relationship between sexual behaviours and subjective HIV infection among the ever-migrated population in Malawi. This presents a significant public health issue for a country battling with multiple disease burden. The findings highlight the need for further research to broaden our understanding of the protective and risk factors underlying subjective HIV infection expectation in Malawi and SSA in general. Importantly, the present study has provided baseline quantitative evidence which can inform further investigation into the association between sexual behaviours, personal feelings and subjective HIV infection in Malawi and other settings where subjective HIV infection have received less attention.

Acknowledgements

The author is grateful to Prof Hans-Peter Kohler, University of Pennsylvania for his assistance with access to the data. The author acknowledges the National Institute of Child Health and Development (grant numbers R03 HD058976, R21 HD050652, R01 HD044228, R01 HD053781), the National Institute on Aging (grant number P30 AG12836), the Boettner Center for Pensions and Retirement Security at the University of Pennsylvania, and the National Institute of Child Health, Development Population Research Infrastructure Program (grant number R24HD-044964) and the pilot funding received through the Penn Center for AIDS Research (CFAR), supported by NIAID AI 045008, and the Penn Institute on Aging all at the University of Pennsylvania for producing the MLSFH data for the study.

Author's contributions

SSS designed the study, analysed and interpreted the data, drafted manuscript, reviewed and approved the final manuscript.

Funding

There was no funding for the study.

Disclosure statement

The author declares that there is no competing interests.

Data availability

The data used for the study could be accessed from https://malawi.pop.upenn.edu/malawi-data-mlsfh.

Ethics approval and consent to participate

Not applicable.

ORCID

Sally Sonia Simmons http://orcid.org/0000-0002-9126-5922

References

Ambler, D. R., Bieber, E. J., & Diamond, M. P. (2012). Sexual function in elderly women: A review of current literature. *Reviews in Obstetrics & Gynecology*, *5*(1), 16–27.

Anglewicz, P. (2012). Migration, marital change, and HIV infection in Malawi. *Demography*, *49*(1), 239–265. https://doi.org/10.1007/s13524-011-0072-x

Anglewicz, P., VanLandingham, M., Manda-Taylor, L., & Kohler, H.-P. (2016). Migration and HIV infection in Malawi. *AIDS (London, England)*, *30*(13), 2099–2105. https://doi.org/10.1097/QAD.0000000000001150

Anglewicz, P., VanLandingham, M., Manda-Taylor, L., Kohler, H.-P. (2018). Health selection, migration, and HIV infection in Malawi. *Demography*, *55*(3), 979–1007. https://doi.org/10.1007/s13524-018-0668-5

Anglewicz, P. A., Bignami-Van Assche, S., Clark, S., & Mkandawire, J. (2010). HIV risk among currently married couples in rural Malawi: What do spouses know about each other?*AIDS and Behavior*, *14*(1), 103–112. https://doi.org/10.1007/s10461-008-9497-7

Bell, A., Fairbrother, M., & Jones, K. (2019). Fixed and random effects models: Making an informed choice. *Quality & Quantity*, *53*(2), 1051–1074. https://doi.org/10.1007/s11135-018-0802-x

Colebunders, R., & Kenyon, C. (2015). Behaviour, not mobility, is a risk factor for HIV. *The Lancet HIV*, *2*(6), e223–e224. https://doi.org/10.1016/S2352-3018(15)00057-0

Curran, P. J., & Bauer, D. J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology*, *62*, 583–619. https://doi.org/10.1146/annurev.psych.093008.100356

Dal Grande, E., Chittleborough, C. R., Campostrini, S., Tucker, G., & Taylor, A. W. (2015). Health estimates using survey raked-weighting techniques in an Australian population health surveillance system. *American Journal of Epidemiology*, *182*(6), 544–556. https://doi.org/10.1093/aje/kwv080

Djamba, Y. K. (1997). Theoretical perspectives on female sexual behaviour in Africa: A review and conceptual model. *African Journal of Reproductive Health*, *1*(2), 67–78. https://doi.org/10.2307/3583377

Dobra, A., Bärnighausen, T., Vandormael, A., & Tanser, F. (2017). Space-time migration patterns and risk of HIV acquisition in rural South Africa. *AIDS*, *31*(1), 137–145. https://doi.org/10.1097/QAD.0000000000001292

Du, P., Crook, T., Whitener, C., Albright, P., Greenawalt, D., & Zurlo, J. (2015). HIV transmission risk behaviors among people living with HIV/AIDS: The need to integrate HIV prevention interventions and public health strategies into HIV care. *Journal of Public Health Management and Practice: JPHMP*, *21*(2), E1–E10. https://doi.org/10.1097/PHH.0000000000000038

Feldacker, C., Emch, M., & Ennett, S. (2010). The who and where of HIV in rural Malawi: Exploring the effects of person and place on individual HIV status. *Health & Place*, *16*(5), 996–1006. https://doi.org/10.1016/j.healthplace.2010.06.004

Fleury, A. (2016). Understanding women and migration: A literature review. *Washington, DC*. (p. 55).

Geubbels, E., & Bowie, C. (2006). Epidemiology of HIV/AIDS in adults in Malawi. *Malawi Medical Journal : The Journal of Medical Association of Malawi*, *18*(3), 111–133.

Golden, S. D., & Earp, J. A. L. (2012). Social ecological approaches to individuals and their contexts: Twenty years of health education & behavior health promotion interventions. *Health Education & Behavior: The Official Publication of the Society for Public Health Education*, *39*(3), 364–372. https://doi.org/10.1177/1090198111418634

Hoffman, L., & Stawski, R. S. (2009). Persons as contexts: evaluating between-person and within-person effects in longitudinal analysis. *Research in Human Development*, *6*(2–3), 97–120. https://doi.org/10.1080/15427600902911189

Holden, J. E., Kelley, K., & Agarwal, R. (2008). Analyzing change: A primer on multilevel models with applications to nephrology. *American Journal of Nephrology*, *28*(5), 792–801. https://doi.org/10.1159/000131102

Jin, H., Wu, S., Vidyanti, I., Di Capua, P., & Wu, B. (2015). Predicting depression among patients with diabetes using longitudinal data. A multilevel regression model. *Methods of Information in Medicine*, *54*(6), 553–559. https://doi.org/10.3414/ME14-02-0009

Jovic, A., Brkic, K., & Bogunovic, N. (2015). *A review of feature selection methods with applications* [Paper presentation]. 2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO) (pp. 1200–1205), Opatija, Croatia. https://doi.org/10.1109/MIPRO.2015.7160458

Kohler, H.-P., Watkins, S. C., Behrman, J. R., Anglewicz, P., Kohler, I. V., Thornton, R. L., Mkandawire, J., Honde, H., Hawara, A., Chilima, B., Bandawe, C., Mwapasa, V., Fleming, P., & Kalilani-Phiri, L. (2015). Cohort profile: The Malawi longitudinal study of families and health (MLSFH). *International Journal of Epidemiology*, *44*(2), 394–404. https://doi.org/10.1093/ije/dyu049

Li, F., Baccini, M., Mealli, F., Zell, E. R., Frangakis, C. E., & Rubin, D. B. (2014). Multiple Imputation by Ordered Monotone Blocks With Application to the Anthrax Vaccine Research Program. *Journal of Computational and Graphical Statistics*, *23*(3), 877–892. https://doi.org/10.1080/10618600.2013.826583

Mandiwa, C., & Namondwe, B. (2019). Uptake and correlates of HIV testing among men in Malawi: Evidence from a national population–based household survey. *BMC Health Services Research*, *19(1), 1-8.*https://doi.org/10.1186/s12913-019-4031-3

Mayer, K., Pizer, H. F., & Venkatesh, K. K. (2008). The social ecology of HIV/AIDS. *The Medical Clinics of North America*, *92*(6), 1363–1375. https://doi.org/10.1016/j.mcna.2008.06.003

McGrath, N., Eaton, J. W., Newell, M.-L., & Hosegood, V. (2015). Migration, sexual behaviour, and HIV risk: A general population cohort in rural South Africa. *The Lancet. HIV*, *2*(6), e252–e259. https://doi.org/10.1016/S2352-3018(15)00045-4

Muhwava, W. (2004). Condom use within marriage and consensual unions in the era of HIV/AIDS in Zimbabwe. *African population studies*, *19*(1), 119–141.

Nutor, J. J., Duah, H. O., Agbadi, P., Duodu, P. A., & Gondwe, K. W. (2020). Spatial analysis of factors associated with HIV infection in Malawi: Indicators for effective prevention. *BMC Public Health*, *20*(1), 1167. https://doi.org/10.1186/s12889-020-09278-0

Oliveira, V. D., & Ferreira, M. A. R. (2011). Maximum likelihood and restricted maximum likelihood estimation for a class of Gaussian Markov random fields. *Metrika*, *74*(2), 167–183. https://doi.org/10.1007/s00184-009-0295-7

Peltzer, K., & Matseke, G. (2013). Determinants of HIV testing among young people aged 18 - 24 years in South Africa. *African Health Sciences*, *13*(4), 1012–1020. https://doi.org/10.4314/ahs.v13i4.22

Poulin, M., & Muula, A. S. (2011). An inquiry into the uneven distribution of women's HIV infection in rural Malawi. *Demographic Research*, *25*, 869–902. https://doi.org/10.4054/DemRes.2011.25.28

Ross, J., Cunningham, C. O., & Hanna, D. B. (2018). HIV outcomes among migrants from low-income and middle-income countries living in high-income countries: A review of recent evidence. *Current Opinion in Infectious Diseases*, *31*(1), 25–32. https://doi.org/10.1097/QCO.0000000000000415

Schafer, J. L. (1999). Multiple imputation: A primer. *Statistical Methods in Medical Research*, *8*(1), 3–15. https://doi.org/10.1177/096228029900800102

Simmons, S. S. (2019). Computational prediction of subjective human immunodeficiency virus status in Malawi using a random forest approach. *AIDS Research and Treatment*, *2019*, 5849183–5849186. https://doi.org/10.1155/2019/5849183

Soley-Bori, M. (2013). Dealing with missing data: Key assumptions and methods for applied analysis. *Boston University*, *23*. (p. 20).

Steele, F. (2008). Multilevel models for longitudinal data. *Journal of the Royal Statistical Society: series A (statistics in society)*, *171*(1), 5-19. https://doi.org/10.1111/j.1467-985X.2007.00509.x

Talenti, L., Luck, M., Yartseva, A., Argy, N., Houzé, S., & Damon, C. (2015). L1 logistic regression as a feature selection step for training stable classification trees for the prediction of severity criteria in imported malaria. *ArXiv:1511.06663 [Cs, q-Bio, Stat]*. http://arxiv.org/abs/1511.06663

Tasca, G. A., Illing, V., Joyce, A. S., & Ogrodniczuk, J. S. (2009). Three-level multilevel growth models for nested change data: A guide for group treatment researchers. *Psychotherapy Research: Journal of the Society for Psychotherapy Research*, *19*(4–5), 453–461. https://doi.org/10.1080/10503300902933188

Vetter, T. R. (2017). Descriptive statistics: Reporting the answers to the 5 basic questions of who, what, why, when, where, and a sixth, so what?*Anesthesia and Analgesia*, *125*(5), 1797–1802. https://doi.org/10.1213/ANE.0000000000002471

Weine, S. M., & Kashuba, A. B. (2012). Labor migration and HIV risk: A systematic review of the literature. *AIDS and Behavior*, *16*(6), 1605–1621. https://doi.org/10.1007/s10461-012-0183-4

Wirth, M. D., Andrew, M. E., Burchfiel, C. M., Burch, J. B., Fekedulegn, D., Hartley, T. A., Charles, L. E., & Violanti, J. M. (2017). Association of shiftwork and immune cells among police officers from the Buffalo Cardio-Metabolic Occupational Police Stress study. *Chronobiology International*, *34*(6), 721–731. https://doi.org/10.1080/07420528.2017.1316732