Resilience, Accelerated Aging and Persistently Poor Health: Diverse Trajectories of Health among the Global Poor

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August 1, 2022

Objectives: This study is among the first to document lifecourse trajectories of physical and mental health across adult and older ages (20–70 years) for a poor sub-Saharan African population having faced frequent and sustained adversities.

Methods: The 2006–19 waves of the Malawi Longitudinal Study of Families and Health (MLSFH) were analyzed using group-based trajectory models (GBTM) to identify trajectories of heath (SF12 mental/physical health and BMI) across the lifecourse. Predictors of trajectory membership were estimated using fractional multinomial logits.

Results: Analyses identified three distinct trajectories: (1) good initial mental/physical health that persisted throughout the lifecourse ("*resilient aging*"); (2) good initial mental and physical health that deteriorated with age ("*accelerated aging*"); or (3) poor initial mental and physical health with possibly further declines over the lifecourse ("*aging with persistently poor health*"). Predictors of trajectory group membership included gender, childhood poverty, and schooling.

Discussion: Despite lifecourses being characterized by poverty and frequent adversities in this poor population, our analyses identified a sizable group (≈30%) of resilient individuals who experienced successful aging with good initial health that persisted across the lifecourse and into old age. Accelerated aging was the most common trajectory for SF12 physical and mental health in this poor population, while for BMI, persistently poor health was most common. Men were more likely to enjoy resilient aging than women in terms of physical/mental health, contrary to previous findings from high-income contexts. Other predictors of trajectory membership sometimes confirmed, and sometimes contradicted, hypotheses derived from high-income country studies.

Keywords: Aging | Health and aging trajectories | Physical health | Mental health | Malawi | GBTM | sub-Saharan Africa | Low-Income Countries

Introduction

Individuals can age at vastly different rates (Ailshire et al. 2015; Kunkel et al. 2019; Levine and Crimmins 2018), and significant within-population heterogeneity can exist in the onset of morbidity and disease as individuals get older (Belsky et al. 2020; Schrempft et al. 2021;

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Vaupel and Yashin 1985; Wrycza and Baudisch 2014). While such aging trajectories have been extensively studied in high-income populations (e.g., Hoang et al. 2021; Walsemann and Ailshire 2020; Zheng et al. 2021), including linking lifecourse disparities in health to early-life contexts or socioeconomic status (Barker 1990; Link and Phelan 1995), the **diversity of aging patterns** has rarely been investigated among poor aging populations who experience substantial hardships throughout the lifecourse. This research gap between high-income and low-income populations is noteworthy as aging in low-income countries (LICs) is often accelerated: substantial declines in physical, mental and cognitive health emerge at younger ages (i.e., during mid-adulthood) compared to higher-income countries (HICs) and extend to older ages (Aboderin and Beard 2015; He et al. 2020; Sudharsanan and Bloom 2018; WHO 2015). Increasing evidence suggests that an earlier onset and faster pace of health decline is a distinctive hallmark of aging in LICs where older adults are often exposed to multiple recurrent adversities throughout the lifecourse (GBD 2019 Disease Collaboration 2020; Kobayashi et al. 2021; Kohler et al. 2017; Payne et al. 2018). Little research, however, has addressed the **variation** in aging trajectories in LICs. For example, are there groups of individuals who, against the odds and despite extensive lifecourse adversities, retain relatively good physical and mental health into old age? And if so, what are predictors of this "resilient aging" in LICs, and do they differ from predictors of resilience in HICs? Similarly, are other groups of individuals particularly vulnerable to the adverse contexts that characterize LICs, and what are their trajectories of "accelerated aging"? Understanding this potential heterogeneity of health trajectories in LICs is critical for assessing the implications of global aging that implies a rapid growth of older individuals in LIC contexts (NASEM 2019), and it is important for devising health policies that facilitate healthy aging among the global poor, while also providing critical support for vulnerable aging populations in LICs (National Academy of Medicine 2022).

This study is among the first to focus on the **diversity** of health trajectories in an aging LIC population that has faced frequent and sustained adversities throughout the lifecourse. Applying group-based trajectory models (GBTM; Nagin 2009; Nagin et al. 2018) to the 2006–19 waves of the Malawi Longitudinal Study of Families and Health (MLSFH Kohler et al. 2015, 2020), our analyses identified three distinct lifecourse health trajectories: (1) good initial mental and physical health that persisted throughout the lifecourse ("**resilient aging**"); (2) good initial mental and physical health that deteriorated during the lifecourse ("**accelerated aging**"); or (3) poor initial mental and physical health that possibly further declined over the lifecourse ("**aging with persistently poor health**").

Importantly, despite lifecourses being characterized by poverty and frequent adversities in this poor population, our analyses identified a sizable group (≈30%) of resilient individuals who experienced successful aging with good initial health that persisted across the lifecourse and into old age. Yet, accelerated aging is the most common trajectory for SF12 physical and mental health in this poor population, while for BMI, persistently poor health is most common as a result of widespread undernutrition. Strikingly, for both phys-

ical and mental health, men are more likely to enjoy resilient aging than women, contrary to previous findings from high-income contexts. Other predictors of trajectory membership sometimes confirm, and sometimes contradict, hypotheses derived from high-income country studies. For example, schooling is positively associated with persistently poor mental health, as well as with accelerated aging in terms of BMI.

Given the overwhelming focus on aging studies on high-income contexts, with only nascent studies in middle-income countries and very limited aging research in LICs, our analyses conclude by highlighting the importance of studying the health and aging trajectories of the global poor to gain a better understanding of how human aging patterns unfold across diverse populations.

Background

Group-based trajectory modelling (GBTM; Nagin 2009; Nagin et al. 2018) has been used to show that there is diversity in aging patterns and health trajectories in HICs. GBTM assumes that the population is composed of a mixture of distinct groups of individuals defined by their developmental trajectories. It identifies groups of individuals following distinct trajectories over time and estimates trajectory parameters (e.g., probability of membership in a group for each individual) separately for each group. This is in contrast to growth curve modeling (Duncan et al. 2013), the most common approach for studying trajectories of health during the aging process, which generally assumes that all individuals in the population follow a similar trajectory that varies around a single mean path. However, the recent literature on the *pace of aging* suggests that this assumption of growth curve models may be inadequate in capturing the *diverse trajectories* that characterize the human aging process and age-related changes in health (Ailshire et al. 2015; Belsky et al. 2020; Levine and Crimmins 2018; Schrempft et al. 2021; Vaupel and Yashin 1985; Wrycza and Baudisch 2014). GBTM avoids this limitation by allowing for different aging trajectories *across* empirically-identified subgroups in a study population, thereby allowing analyses to document more complex heterogeneity in aging patterns that remains undiscovered by growth curve modeling approaches.

Prior research using GBTM for instance found seven distinct health trajectories for body mass index (BMI) for individuals between ages 31–80 in the Framingham Heart Study (Zheng et al. 2021), including one (with 24% of individuals) that maintained normal weight throughout adulthood. Liang et al. (2011) examined trajectories for depressive symptoms among adults aged 50+ years in the Health and Retirement Study (HRS) over an 11-year period, identifying individuals with minimal (16%) and low (26%) initial depressive symptoms that persisted as individuals aged. Many other studies have identified groups of individuals with stable physical and mental health trajectories in HICs (Andreescu et al. 2008; Byers et al. 2012; Mallett et al. 2022; Musliner et al. 2016; Song et al. 2018; Yang et al. 2019; Zheng et al. 2013).

The distinct health trajectories identified by GBTM in HICs, however, may not general-

ize to LICs with vastly different socioeconomic and epidemiological contexts. For instance, the individuals we study have lived most of their life in a subsistence-agriculture context with incomes of less than one-dollar-a-day (Malawi National Statistical Office 2018). Older members of the cohort were born when under-5 mortality was almost 30% (UN Population Division 2022) and have survived though frequent adversities as a result of poverty, famine and epidemics, including the HIV/AIDS epidemic that devastated much of the sub-Saharan African region. These socioeconomic contexts experienced by our and other global-poor study populations are vastly different from the lifecourse contexts experienced by the study populations used for the overwhelming majority of aging studies or studies investigating lifecourse trajectories of health. Yet, studying global poor populations is important because the world's aging populations are increasing concentrated in such contexts and the different socioeconomic contexts may have implications for health across the lifecourse. For example, in our study population, high blood pressure is common among older individuals despite the lack of conventional risk factors such as obesity or western diets (Kohler et al. 2020, 2022c). Declines in physical and mental health occur on average in this cohort at younger ages as compared to individuals in HICs (Kohler et al. 2022a,b), and similar patterns of early health declines have been documented in other populations exposed to significant lifecourse adversities (Geronimus et al. 2006; Phelan and Link 2015; Simons et al. 2021). Global aging research is also only starting to document the determinants and correlates of trajectories of later-life health and aging in LICs (NASEM 2019; National Academy of Medicine 2022).

Data and Methods

The Malawi Longitudinal Study of Families and Health (MLSFH): The MLSFH is one of a few long-standing publicly available cohort studies in the low-income context of sub-Saharan Africa (SSA LIC) (Kohler et al. 2015, 2020). MLSFH is conducted in rural areas in three districts (Mchinji in the Central, Rumphi in the Northern and Balaka in the Southern regions). Between 1998–2021, MLSFH has collected 12 rounds of data with extensive lifecourse, socioeconomic and health information about the study participants. MLSFH respondents who migrated to urban centers and other locations in Malawi are also followed up longitudinally by MLSFH. Although not drawn as a nationally representative sample in 1998, MLSFH broadly represents the rural population in Malawi, where about 85% of all Malawians reside. The study closely matches the rural sub-sample in the 2010 nationally representative Integrated Household Survey 3 (Malawi IHS 2017) in key observed characteristics. Cohort profiles (Kohler et al. 2015, 2020) provide detailed information about sampling, study instruments, and attrition. Most of the MLSFH cohort members living in these rural areas engage in manual, intensive physical labor such as home production of crops, complemented by some market activities.

While the broad demographic, socioeconomic and epidemiological conditions are fairly similar across the three MLSFH study regions, and also across other parts of rural Malawi,

some noteworthy differences across the MLSFH regions include the following. The northern district with Rumphi is inhabited primarily by Tumbukas, who are predominantly Protestant, and follows the patrilineal system of kinship and lineage where residence is primarily patrilocal. Mchinji District (Central Region) follows a less rigid matrilineal system whereby residence may be matrilocal or patrilocal or neither (among MLSFH participants in Mchinji, about 75% follow patriolocal traditions). It is primarily inhabited by Chewas, with almost equal proportions of Catholics and Protestants. Balaka District (Southern Region) is primarily inhabited by Lomwes and Yaos and has the highest proportion of Muslims. The region follows a matrilineal system of kinship and lineage system where residence is ideally matrilocal, although it is not uncommon for wives to live at least some time in their husbands' villages. The Balaka region also exhibits lower ages of sexual debut and larger numbers of lifetime sexual partners than the other MLSFH study regions, and residents tend to be less educated and poorer than those living in the north (see cohort profiles in Kohler et al. 2015, 2020, for additional details).

Strengths of the MLSFH for the analyses in this study include the availability of longitudinally measured health indicators that cover aspects of physical and mental health. This extensive health information spans over two decades and provides valuable insights from a life-course perspective on how individuals age in this context. Moreover, MLSFH also reflects considerable heterogeneity of social, demographic and cultural contexts across rural Malawi that reflect much of the diversity that exists in sub-Saharan Africa.

Health Measures: We used the Short Form 12-item (SF12) mental and physical health scales, which range from 0 to 100 (worst to best health). The SF12 scales are widely used and validated measures of overall physical and mental health (Gandek et al. 1998; Ohrnberger et al. 2020). The original SF12 scores were standardized to have a mean score of 50 and a standard deviation of 10 in the general U.S. Population (Ware et al. 2001), and in the overall MLSFH population (2010 round), the means are similar with 50.1 (physical; SD = 9.2) and 52 (mental; SD = 9.7). A score of 50 or less on SF12 physical has been recommended as a cut-off to determine a physical condition, while a score of 42 or less on the SF12 mental may be indicative of clinical depression(Ware et al. 2001). We also used body mass index (BMI; kg/m2) as another measure of physical health. Both height and weight were measured by trained MLSFH study personnel.

Correlates of Group Membership: We examined the correlates of demographic factors and socioeconomic status with the probability of belonging to a particular trajectory. Demographic variables consisted of indicators for being male and for region of birth. Childhood socioeconomic status was measured by an indicator variable for childhood poverty equal to 1 if the primary reason for not attending or completing primary school was that parents could not afford the schooling fees. Otherwise, the indicator variable is 0 including all cases when primary education was completed. Adult socioeconomic was measured by schooling attainment.

Table 1: Summary Statistics for SF12 mental/physical health analyses sample ($N = 3,707$)

	Women Proportion	**Men** Proportion	**Total** Proportion	N
Male	0.00	1.00	0.42	3,707
Born North	0.30	0.29	0.29	3,707
Born Central	0.34	0.36	0.35	3,707
Born South	0.35	0.34	0.34	3,707
Born Abroad	0.01	0.01	0.01	3,707
Childhood poverty	0.49	0.61	0.54	3,205
Less than Primary Schooling	0.30	0.17	0.25	3,706
Primary Schooling	0.61	0.64	0.62	3,706
Secondary Schooling or more	0.08	0.20	0.13	3,706

Analytical Sample: The analysis was restricted to (a) the 2006–2018 MLSFH waves because the SF12 scales were collected from 2006 onwards and (b) individuals who had at least two observations on the health measures. Our analytical sample for analysis of SF12 (BMI) consists of 3,707 (2,363) individuals. The SF12 (BMI) analytical sample has 3.9 (3.2) observations on average per individual, yielding a total of 14,618 (7,474) person-year observations. Table 1 reports summary statistics of the correlates for the sample used to estimate trajectories of the SF12. The summary statistics for the BMI sample are reported in the Supplemental Material (Table S.1). In comparison, the two samples are not very different. 42% of the sample is male and born in one of the three regions in Malawi with roughly equal proportions. Overall, more than half of the sample reported having experienced poverty during childhood. 61% of men and 49% of women grew-up in poor households. A quarter of individuals has less than primary education and close to 90% has no more than primary education. 30% of women have less than primary schooling and 8% of women have completed secondary schooling or more. In contrast, 17% of men have less than primary schooling and 20% have secondary schooling or more.

Tables 1 and S.1 also report the total number of non-missing observations by variable. 14% of the analytical SF12 sample and 3% in the BMI sample have missing data on childhood poverty. In those cases, we compute the mean of childhood poverty by trajectory group and gender and use this value for imputation.

Statistical Methods: The analysis consisted of two parts. We first used GBTM—a specialized application of finite mixture modeling—to identify latent health trajectories (Nagin 2009; Nagin et al. 2018; see **Supplemental Materials** for additional details). GBTM uses maximum likelihood to identify groups of individuals with statistically similar trajectories. We modelled trajectories with a quadratic in age and used the censored normal distribution for all outcomes. GBTM provides (1) a predicted shape for each trajectory, (2) the estimated proportion of the sample at baseline that belong to each group and (3) for each individual the estimated probability of belonging to each group (posterior probabilities). Basic GBTM assumes independence of probabilities of group membership and attrition, leading to bi-

ased trajectory group membership when attrition is nonrandom. To overcome this limitation, we used the generalized enhanced GBTM application developed by Haviland et al. (2011), which models the joint estimation of trajectories and the probability of nonrandom dropout. The dropout model calculates a trajectory-specific dropout probability based on prior wave observations and adjusts group-specific membership probabilities. We modelled dropout as a function of gender, birth region, childhood poverty, adult schooling attainment and observed outcome and age at the previous wave. Inferences about the optimal number of trajectories were made following the criteria laid out in Nagin (2009). The model fit statistics are presented in the supplementary materials. The GBTM analysis was carried out in Stata 15 with the `traj` plugin (Jones and Nagin 2013).

After estimating the trajectories, we computed for each individual the posterior probabilities of belonging to each of the trajectory groups where the probabilities for each individual sum to 1. We departed from the usual approach of assigning individuals to a single trajectory according to the maximum posterior probability rule as this rule ignores the information contained in the posterior *distribution*. Our approach recognizes that individuals have different propensities of belonging to each of the trajectories, and we utilize this information. Specifically, we estimated fractional multinomial logit (FML) regressions to study the correlations of demographic factors and socioeconomic status with the posterior probabilities. The FML is an extension of the multinomial logit to responses that are fractional (between 0 and 1), instead of binary, and sum to one (Mullahy 2015). This approach uses the complete information contained in the posterior distribution and avoids the loss of information entailed by assigning individuals to a single trajectory. A further advantage of FML is that the marginal effects sum to zero across the outcomes (in any discrete distribution, a increase in the probability of one outcome needs to be associated with a corresponding decline in the probabilities of other outcomes). Our FML regressions were implemented in Stata 15 with the `fmlogit` plugin (Buis 2008).

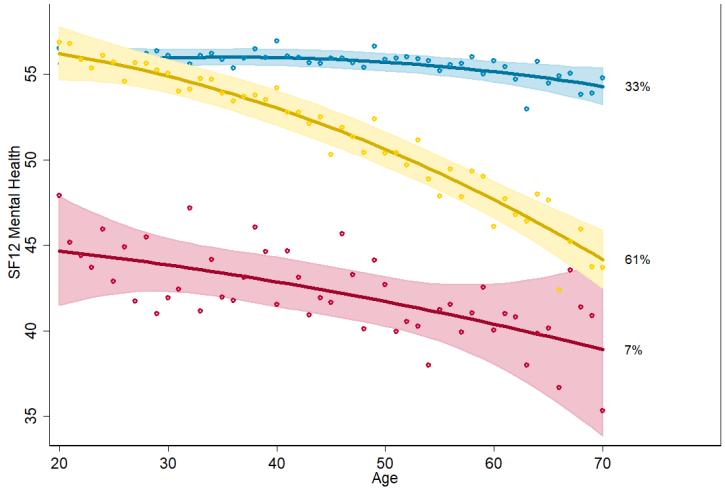
Results

Mental Health and Physical Health Trajectories: Our analyses identified three distinct trajectories for each health measure. For SF12 mental health (Figure 1a), two trajectory groups had good initial mental health, indicated with scores above 55. For 33% of individuals the SF12 mental health score was stable through adulthood, whereas it declined sharply over the whole age range for another group to which 61% of individuals belonged. We refer to these two trajectories as **resilient aging** (blue in Fig. 1a) and **accelerated aging** (yellow), respectively. The lowest trajectory group only had 7% of individuals belonging to it, and was less precisely estimated with a wider 95% confidence interval. This group had an initial SF12 score of about 45, which declined steadily over the whole age range; we therefore refer to it as the trajectory group with **persistently poor health** (red in Fig. 1a).

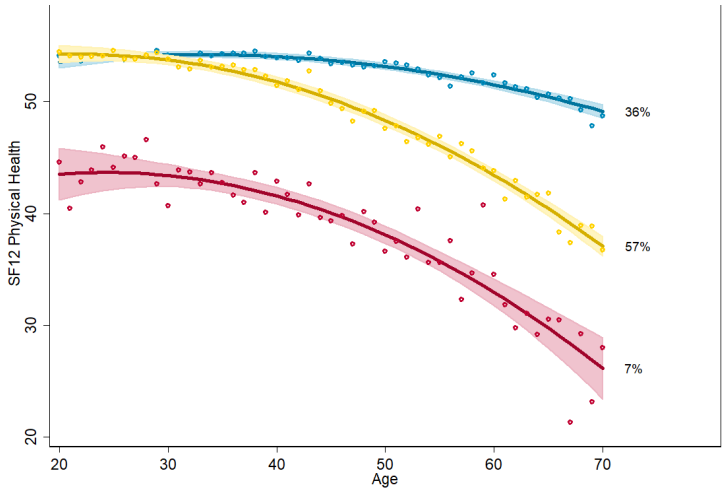
Trajectories for SF12 physical health (Figure 1b) mirrored those for SF12 mental health. Individuals that follow the trajectory of resilient aging (36%; blue in Fig. 1b) and accel-

Figure 1: Trajectories of health across the lifecourse: resilient aging (blue), accelerated aging (yellow) and persistently poor health (red)

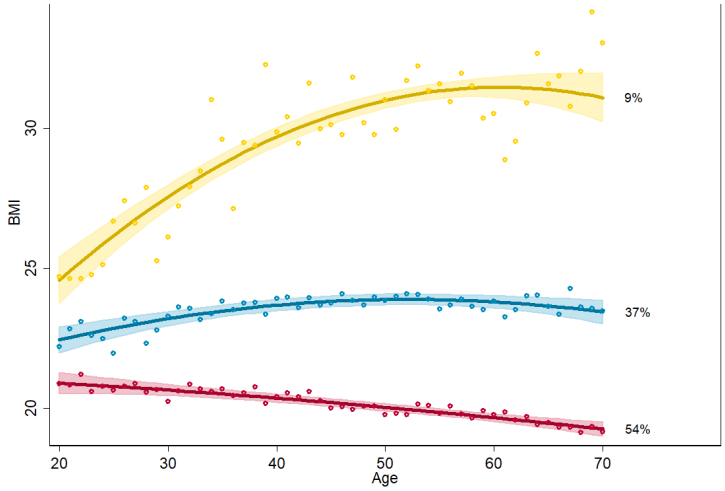
(a) SF12 Mental Health



(b) SF12 Physical Health



(c) BMI



erated aging (57%; yellow) both started with good physical health with scores above 50. This relatively good health persisted for the resilient aging group until about age 50, and thereafter declined slightly. For the accelerated aging group, the SF12 physical health score followed a steep decline as individuals age and progress from mid-adulthood to old ages (age 30–70). 7% of respondents followed the persistently poor health trajectory (red in Fig. 1b) that is characterized by already fairly poor health in early/mid adulthood and then subsequent further declines during late adulthood and old age.

For BMI (Figure 1c) the two lowest trajectory groups both started with BMI in the normal range ($18.5 \leq \text{BMI} < 25$) at age 20. BMI for the trajectory group with 54% of individuals steadily declined with age (**persistently poor health**; red in Fig. 1c), whereas it increased with age but remained in the normal range for the trajectory group with 37% of individuals (**resilient aging**; blue). The third trajectory group had 9% of individuals. At age 20, BMI was just below 25 and thus in the normal range. There was a sharp increase in BMI between ages 20-50 and individuals on this trajectory were classified as obese ($\text{BM} \geq 30$) after age 50 (**accelerated aging**; yellow in Fig. 1c).

Predictors of Trajectory Group Membership: Marginal effects (evaluated at the means) from FML regressions are presented in Table 2. The predictive power of demographic factors for trajectory group membership of the SF12 mental and physical health components were similar. Men were 12% (14%) more likely to belong to resilient aging trajectories for SF12 mental (physical) health than women. Region of birth did not predict trajectory group membership for mental health, but being born in the North region was associated with a significant 2.5% increase in the probability of following the trajectory of accelerated aging and a 2% decrease in the probability of belonging to the trajectory group with persistently poor health.

The influence of childhood poverty and schooling attainment differed across SF12 outcomes. Childhood poverty was associated with a 3% decrease in the probability of belonging to the trajectory of resilient aging for mental health, and a 2% (1%) higher probability of belonging to the accelerated aging (persistently poor health) trajectory. Childhood poverty did not statistically significantly predict trajectory group membership for physical health. More schooling was associated with a higher likelihood of being on the physical health resilient aging trajectory, and lower likelihoods of being on the accelerated aging and persistently poor health trajectories. For examples, individuals who completed primary schooling were 4% more likely to be on the resilient aging trajectory, and 2% less likely to be on the accelerated aging trajectory compared to individuals with who did not complete primary schooling. For mental health, counter intuitively individuals who completed primary schooling were 2% more likely to belong to the persistently poor health trajectory compared to individuals who did not complete primary schooling.

For BMI, men were more likely to belong to the trajectory group of persistently poor health with BMI in the range 19-21 throughout adulthood. Childhood poverty had no significant association with group membership to any of the BMI trajectories. Higher school-

Table 2: Associations of Demographic Characteristics and Socioeconomic Status with Trajectory Group Membership

Outcome	SF12 Mental Health			SF12 Physical Health			BMI		
Trajectory Group	Resilient Aging	Accelerated Aging	Persistently Poor Health	Resilient Aging	Accelerated Aging	Persistently Poor Health	Resilient Aging	Accelerated Aging	Persistently Poor Health
Group Membership	33%	61%	7%	36%	57%	7%	37%	9%	54%
Male	0.116***	-0.054***	-0.061***	0.136***	-0.074***	-0.062***	-0.102***	-0.106***	0.207***
	(0.009)	(0.007)	(0.005)	(0.010)	(0.010)	(0.006)	(0.017)	(0.011)	(0.018)
Born South	0.002	-0.007	0.006	0.009	-0.005	-0.003	-0.032	0.003	0.029
	(0.011)	(0.009)	(0.005)	(0.011)	(0.010)	(0.007)	(0.021)	(0.013)	(0.026)
Born North	-0.003	0.000	0.002	-0.005	0.025**	-0.020**	0.016	0.033***	-0.049**
	(0.011)	(0.008)	(0.007)	(0.012)	(0.010)	(0.009)	(0.022)	(0.011)	(0.024)
Born Abroad	-0.009	0.009	0.000	-0.014	0.002	0.012	-0.031	0.053*	-0.022
	(0.047)	(0.040)	(0.027)	(0.041)	(0.038)	(0.023)	(0.062)	(0.028)	(0.062)
Primary Schooling	-0.011	-0.005	0.016***	0.037***	-0.024*	-0.013*	0.076***	0.031**	-0.106***
	(0.011)	(0.010)	(0.006)	(0.014)	(0.014)	(0.007)	(0.017)	(0.012)	(0.019)
Secondary Schooling or more	-0.007	-0.010	0.017	0.054***	-0.032**	-0.022	0.093***	0.067***	-0.159***
	(0.015)	(0.012)	(0.010)	(0.018)	(0.015)	(0.015)	(0.030)	(0.018)	(0.031)
Childhood Poverty	-0.028***	0.016**	0.012*	0.011	-0.009	-0.002	0.027	-0.002	-0.026
	(0.009)	(0.007)	(0.007)	(0.011)	(0.009)	(0.006)	(0.018)	(0.009)	(0.018)
Observations	3707	3707	3707	3707	3707	3707	2363	2363	2363

Note: Marginal effects evaluated at the mean from FML regressions where the probability of individual i belonging to trajectory group j is regressed on gender, region of birth indicators, year of birth indicators, and indicators for child poverty and schooling attainment. Standard errors clustered at the village level. ***p<0.001 **p<0.05 *p<0.10.

ing attainment was associated with a higher probability of belonging to the resilient aging trajectory, and a lower probability of belonging to the persistently poor health trajectory. In particular, individuals who completed primary school were 8% (11%) more (less) likely to belong to the resilient aging (persistently poor health) trajectory than those who did not complete primary schooling. Individuals who completed primary schooling though were also 3% more likely to be on the accelerated aging trajectory compared to individuals who did not complete primary schooling.

Conclusions

Though average health deteriorates with age almost universally as a basic feature of the human lifecourse (Kunkel et al. 2019), studies documenting the heterogeneity and diversity of aging patterns have concentrated on high-income countries (HICs) (e.g., Hoang et al. 2021; Walsemann and Ailshire 2020; Zheng et al. 2021). A key insight emerging from these HIC studies as been the existence of distinct aging trajectories, wherein some groups of individuals experience worsening health over their lifecourses, while others are resilient and have (relatively) stable health trajectories and thus exhibit healthy—or resilient—aging (Ailshire et al. 2015; Newman and Murabito 2013).

Our analyses extend these investigations to a low-income-country (LIC) to identify if such resilient groups of individuals with relatively stable health trajectories also exist in contexts where poverty and adversities are common across the lifecourse. The answer to this question is unclear from the previous literature as prior evidence from HICs is not necessarily generalizable to LICs where individuals face vastly different economic and social contexts, and where accelerated aging entails that declines in physical health tend to occur on average at younger ages compared to HICs. No prior studies to our knowledge have examined heterogeneous aging patterns in such low-income contexts.

This study employed GBTM to identify latent mental and physical health trajectories from ages 20–70 for individuals in the MLSFH. Our analysis indicated three trajectory groups that followed distinctive patterns of health and aging across the adult and older-age lifecourse. One trajectory, which we label **aging with persistently poor health**, started with low mental/physical SF12 scores or BMI in early/mid adulthood and was characterized by further declines thereafter as individuals got older. Yet, the group exhibiting this trajectory had the smallest group membership in our analyses ($\approx$7%) for the self-reported outcomes (SF12 mental/physical health). In contrast, as one might expect given poverty levels and often insufficient nutrition (Malawi NSO 2018), a large fraction (54%) of individuals were on this trajectory for BMI.

The other two groups both had trajectories that started with good mental and physical SF12 scores or normal BMI in early/mid adulthood, with subsequently stark differences emerging during midlife to old age. In a trajectory that we label **resilient aging**, individuals maintained relatively good health—measured by physical/mental heath SF12 and BMI—throughout the lifecourse and into old age. This pattern was in sharp contrast to

the **accelerated aging** trajectory on which relatively good early/mid adulthood health was followed by rapidly declining health as individuals got older. For physical and mental health (SF12), about 1.6–1.8 times as many individuals in this LIC population belonged to the group following the accelerated aging trajectory as compared to the group with the resilient aging trajectory (61% vs 33% for mental, and 57% vs. 36% for physical health). For BMI, only about 10% of individuals were on this accelerated aging trajectory that was characterized by an increasing BMI with the average reaching obesity by about age 50. This fraction is likely to increase in future cohorts as obesity further spreads also in rural LICs (Ford et al. 2017).

Several key insights emerge from these GBTM analyses. First, **accelerated aging** was widespread in this LIC population in terms of self-reported physical and mental health, while in terms of BMI, it was (still) relatively rare as a result of poor average nutrition and the absence of widespread Western diets in this rural Malawi population. Second, and noteworthy given the widespread and frequent lifecourse adversity that this LIC population has experienced, a sizable subset of individuals followed the **resilient aging** trajectory with relatively good health from early/mid-life into older ages. Across all three outcomes, approximately 1/3 of our study population followed this resilient aging trajectory with "relatively healthy" aging. Third, only a relatively small fraction of individuals followed the **aging with persistently poor health** trajectory for self-reported physical and mental health, while for BMI, this trajectory was common.

Hence, not unlike the HIC populations studied in prior trajectory analyses, our LIC study population from Malawi is characterized by distinct and heterogeneous aging trajectories that were identified in all three outcomes analyzed here. Importantly, this diversity of aging pattern implies that persistently poor health or accelerated aging are not inevitable predicaments in this LIC population; in contrast, our findings suggest a sizable subset of individuals enjoyed resilient ("relatively healthy") aging despite poverty and frequent adversities throughout the lifecourse.

In addition, our analyses of trajectory group membership, summarized in Table 3, highlight the long arm of early-life conditions and gender in determining aging trajectories. The associations we document in this LIC population sometimes confirm, but sometimes also contradict, the hypothesized associations based on HIC studies (Column 1 in Table 3). Evidence from HICs generally documents women to have greater longevity and better health at older ages (Austad 2011), and based on this HIC experience one might thus expect men to be less likely to experience resilient aging, and more likely to follow the accelerated aging or persistently poor health trajectories. Childhood poverty or adversity in HICs are generally found to be risk factors for poor health in later life (Geronimus et al. 2006; Monaghan and Haussmann 2015), thereby increasing the risk of being on the accelerated aging or persistently poor health trajectories. Schooling is generally found to be protective (Link and Phelan 1995; Walsemann and Ailshire 2020), thus decreasing the risk of being on these trajectories, while increasing the likelihood of resilient aging.

Table 3: Predictors of trajectory group membership

		MLSFH Trajectory Analyses		
	Hypothesized Association (HIC studies) (1)	SF12 **Mental Health** (2)	SF12 **Physical Health** (3)	**BMI** (4)
Resilient Aging				
Male	−	++	++	−−
Childhood Poverty	−	−−		
Schooling	+		++	++
Accelerated Aging				
Male	+	−−	−−	−−
Childhood Poverty	+	++		
Schooling	−		−−	++
Persistently poor health				
Male	+	−−	−−	++
Childhood Poverty	+	+		
Schooling	−	++	−	−−

Color coding indicates if associations in Columns 2–4 are in expected/unexpected direction based on HIC research (Column 1): **Blue:** association in expected direction based on HIC research. **Red:** association in unexpected direction based on HIC research. **Black:** no strong prior about direction of association.

While our analyses documented marked gender differences in group membership and aging trajectories, contrary to the expectation based on HIC studies, our analyses found that health of men was often better and/or declined less rapidly with age (Columns 2–4 in Table 3). For physical and mental health, for example, men were less likely to be on the persistently poor health or accelerated aging trajectories; for BMI, men were less likely to follow the accelerated aging trajectory. Related findings documenting men to have better health than women at older ages in other MLSFH studies of mental health and cognition (Kohler et al. 2020, 2017; Payne et al. 2018). While we cannot identify the specific mechanisms underlying these reverse gender patterns in this paper, they were likely related to socioeconomic gender inequalities that disadvantaged women more in the LIC studies than in HICS and/or due to consequences of high fertility and often poor reproductive health in these cohorts compared to HICs.

In terms of schooling and childhood poverty, our analyses indicate that some well-established associations with later-life health from HIC studies do indeed generalize to LICs (Columns 2–4 in Table 3). In particular, for SF12 mental health, childhood poverty was associated with a *lower* likelihood of resilient aging trajectory. Similarly, for SF12 physical health and BMI, higher adult schooling attainment was associated with an *increased* probability of following the resilient aging trajectory. These associations are consistent

with the notion that that SES and schooling are fundamental causes of health disparities (Link and Phelan 1995), and our analyses show that these factors were associated with lifecourse health and aging trajectories also in this LIC population.

However, not all of our findings are in the direction that might be expected based on HIC studies (Columns 2–4 in Table 3). Importantly, for mental health we found that schooling was associated with a *higher*—rather than a lower—probability of belonging to the persistently poor health trajectory. For BMI, our analyses show that schooling is predictive of accelerated aging. This finding is also contrary to expectations based on HIC studies, but it is consistent with recent comparative analyses showing that in LICs higher levels of schooling tend to be associated with increased risks of obesity, while in HICs, the schooling–obesity relationship is reversed (Frankenberg et al. 2016).

Overall, our above findings emphasize the importance of studying health and aging trajectories among the global poor. Aging in rich and poor populations differs not simply in terms of life expectancies and health at various ages (GBD 2019 Disease Collaboration 2020). Instead, the aging process itself is likely to start diverging in early life, with differences accumulating into old age as a result of the interactions of behaviors, social contexts and environments (Glass and McAtee 2006; Harris and McDade 2018). The factors having the largest imprint on aging in LICs might be different from those in HICs (Bell et al. 2019; Halfon et al. 2018), and distinct LIC social contexts, including some that might increase resilience (e.g., social integration of the old), imply that the lifecourse determinants of later-life health in LICs are potentially different from those documented in higher-income contexts (Castro Torres et al. 2021). Ultimately, to understand and improve aging among the global poor, and to understand patterns of aging across the spectrum of economic development, analyses need to include studies in low-income contexts. Yet, so far, only very few aging studies focus on the global poor. This paper illustrates some of the novel findings that can emerge from such studies.

Our analyses have some noteworthy limitations. While our analyses documented some distinctive—as well as some similar—trajectories of aging and health between LICs and HICs, and sometimes distinctive factors associated with belonging to these trajectories, our analyses are correlational and cannot document the mechanisms why aging trajectories in LICs sometimes differ from those in HICs, and sometimes do not differ; neither can our analyses identify the mechanisms that underlying why some—but not all—socioeconomic determinants of health in LICs have different associations with lifecourse trajectories of health than in HICs. Despite these limitations, our analyses are important because they help document the similarities and differences between LICs and HICs in health and aging lifecourse trajectories and their antecedents. As more LIC aging data become available, future analyses will be able to unpack the underlying mechanisms and pathways. An additional limitation of our analyses is that, although we have longitudinal data over long segments of the adult life course, we do not have physical and mental health data starting in early life so we could not investigate health trajectories over complete life courses.

A further limitation is that among our three outcome measures, only BMI is measured and SF12 mental and physical health are self-reported. However there is a long literature documenting that self-reports have significant predictive power for longer-run health outcomes such as mortality (Idler et al. 1992; Torres-Collado et al. 2022; Wuorela et al. 2020)). We also have limited demographic and SES measures from early life for predicting trajectory group membership in adulthood. However, no other data in a sub-Saharan African LIC would allow analyses by combining data on early-life influences with longitudinal health measures stretching from adulthood into old age. By relying on MLSFH data that are exceptional for LICs, even though they have limitations, we make important contributions to our understanding of health and aging trajectories and their correlations with important child and youth demographic and SES measures over long segments of the life course for the first time for a low-income context.

Acknowledgments: We gratefully acknowledge the generous support for the Malawi Longitudinal Study of Families and Health (MLSFH) by by the National Institute of Child Health and Human Development (NICHD, grant numbers R03 HD05 8976, R21 HD050653, R01 HD044228, R01 HD053781, R01 HD087391), the National Institute on Aging (NIA, grant numbers R21 AG053763 and P30 AG 12836), with complementary funding for the MLSFH Mature Adults Cohort through the Swiss Programme for Research on Global Issues for Development (SNF r4d grant 400640_160374).

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Supplemental Material

Group-based Trajectory Modeling

GBTM is a specialized application of finite mixture modelling aiming to identify groups of individuals with statistically similar developmental patterns or trajectories (Nagin et al. 2018). Because of high mortality in Malawi (UN Population Division 2022), we use an extension of the GBTM model that takes into account nonrandom attrition due to mortality.[1] In the basic GBTM model, let $\mathbf{Y_i} = y_{i1}, y_{i2}, ..y_{iT}$ represent the longitudinal sequence of outcomes and $\mathbf{Age_i}$ represent individual i's age when each of those outcomes is recorded (i.e. age_{it}). The distribution of the outcome is denoted $P(\mathbf{Y_i}|\mathbf{Age_i})$. GBTM assumes that there are J underlying trajectory groups. The likelihood for each individual i conditional on the number of groups J is given by equation (1), where π_j is the probability of membership in group j.

$$P(Y_i|age_i) = \sum_{j=1}^{J} \pi_j P(Y_i|age_i, j) \tag{1}$$

The model assumes that the random variables y_{it} are independent conditional on membership in group j. The likelihood can thus be written as,

$$P(Y_i|age_i, j) = \prod_{t=1}^{T} p(y_{it}|age_{it}, j) \tag{2}$$

where $p(.)$ is the distribution of y_{it} conditional on membership in group j and the age of individual i at time t. We assume a censored normal distribution for all of our outcomes and the trajectories are modelled with a polynomial function of age.

$$y_{it}^{*} = \beta_0^j + \beta_1^j age_{it} + \beta_2^j age_{it}^2 + u_{it} \tag{3}$$

where $\beta_0, \beta_1, \beta_2$, are parameters that determine the shape of trajectory j and u_{it} is an error term. Each trajectory is estimated using a unique set of parameters. The basic model provides a predicted shape for each trajectory, an estimated proportion of the sample at baseline that most likely belong to each group, and for each individual the estimated probabilities of belonging to each group (posterior probabilities of group membership).

The basic model assumes that trajectory group membership is independent of attrition. Haviland et al. (2011) have extended the basic model to allow the dropout probability to vary as a function of observed outcomes prior to dropout and covariates. The elements of $\mathbf{Y_i}, y_{it}$, are redefined to incorporate dropout information. As before y_{it} equals its realized value prior to dropout. At the time of dropout and thereafter y_{it} is designated as missing. The revised likelihood specifies the joint probability of realized values prior to dropout

[1] Attrition from MLSFH due to refusal to participate in the study, loss to follow-up not related to mortality is relatively low; for example, follow-up rates among surviving mature adults are very high (97% during 2012–18) and refusal rates are very low (<3% during 2017–18) (Kohler et al. 2015, 2020).

and their missingness thereafter.

Suppose that individuals are measured over a total of T measurement occasions. Let $w_{it} = 1$ if individual i dropped out by $t \leq T$ and 0 otherwise; τ_i the period $t > 1$ that individual i drops out and $T + 1$ if individual i does not drop out; and θ_t^j= the probability of dropout in period $2 \leq t \leq T$ given membership in group J. The probability of dropout is dependent over time since $w_{it} = 0$ in a given period implies $w_{it} = 0$ in prior periods. Similarly, $w_{it} = 1$ in a given period implies $w_{it} = 1$ in subsequent periods. To account for dropout at $\tau_i < T + 1$ and for the attendant data censoring, equation (2) must be altered. For each period up to τ_i for which there are data, the probability of the observed outcome given membership in group j is $p(y_{it}|w_{it} = 0, age_{it}, j)(1 - \theta_t^j)$. Multiplying across $\tau_i - 1$ periods prior to dropout for which there are data the probabilities become $\prod_{t=1}^{\tau_i - 1} p(y_{it}|w_{it} = 0, age_{it}, j)(1 - \theta_t^j)$. Finally, to account for censoring due to dropout from period τ_i onward, this probability must be multiplied by the probability of dropout at $\tau_i, \theta_{\tau_i}^j$. Equation (2) in its more general form is:

$$P(Y_i|age_i, j) = \prod_{t=1}^{\tau_i - 1} [p(y_{it}|w_{it} = 0, age_{it}, j)(1 - \theta_t^j)]\theta_{\tau_i}^j \tag{4}$$

Equation (4) is substituted into equation (1) to form the unconditional likelihood for individual i which is maximized. The model allows θ_t^j to vary by trajectory and within trajectory groups across time, as well as specifying θ_t^j as a function of covariates. We model the dropout probability as a function of the outcome prior to dropout, gender and education using the logit distribution.

Inferences about the optimal number of trajectories are made using the combination of criteria laid out in Nagin (2005): (i) the Bayesian information criterion (BIC), with lower absolute values indicating a better fit; (ii) the log Bayes factor ($2\,\Delta$ BIC) > 10; (iii) trajectory group size $\geq 5\%$ of the sample; (iv) average posterior probability (AvePP) > 0.70; (vi) the odds of correct classification (OCC) > 5 for all groups; and (vii) model interpretability. The GBTM analysis was conducted using the `traj` command in Stata version 15.

Table S.1: Summary Statistics for BMI Analyses Sample ($N = 2,363$)

	Women	**Men**	**Total**	
	Proportion	Proportion	Proportion	N
Male	0.00	1.00	0.39	2,363
Born North	0.31	0.31	0.31	2,363
Born Central	0.33	0.38	0.35	2,363
Born South	0.35	0.29	0.33	2,363
Born Abroad	0.02	0.02	0.02	2,363
Childhood poverty	0.53	0.65	0.57	2,261
Less than Primary Schooling	0.35	0.18	0.28	2,363
Primary Schooling	0.60	0.64	0.62	2,363
Secondary Schooling or more	0.05	0.17	0.10	2,363

Table S.2: Bayesian Information Criterion

Outcome / Trajectory	BIC	Log Bayes Factor
BMI		
2	-18,967	
3	-18,312	1,310
4	-17,998	628
SF-12 Physical Health		
2	-50,022	
3	-49,821	402
4	-49,807	28
SF-12 Mental Health		
2	-53,251	
3	-53,225	52
4	-53,232	-14

Table S.3: Group Membership

Outcome / Trajectory	% Estimated	% Assigned	% Estimated	% Assigned	% Estimated	% Assigned
BMI						
1	85.1	85.8	54.0	55.0	11.6	10.8
2	14.9	14.2	37.1	36.6	41.0	42.0
3			8.9	8.4	43.6	43.4
4					3.8	3.8
Weighted Diff.	0.7		0.8		0.6	
SF-12 Physical Health						
1	14.0	11.7	7.1	7.0	3.5	3.1
2	86.0	88.3	57.1	73.5	55.3	74.8
3			35.9	19.5	33.0	15.9
4					8.1	6.2
Weighted Diff.	2.3		15.3		17.4	
SF-12 Mental Health						
1	83.0	87.2	60.9	77.7	5.2	3.1
2	17.0	12.8	32.5	16.8	29.2	13.3
3			6.6	5.4	59.9	79.8
4					5.7	3.7
Weighted Diff,	4.2		15.8		18.1	

Table S.4: Average Posterior Probability and Odds of Correct Classification

Outcome / Trajectory	Average Posterior Probability			Odds of Correct Classification		
BMI						
1	97.7	89.6	84.6	7.4	7.3	42.0
2	91.0	84.5	82.5	57.7	9.2	6.8
3		94.0	88.3		161.0	9.8
4			91.7			279.6
SF-12 Physical Health						
1	87.1	83.4	78.0	41.5	65.9	98.3
2	95.7	71.4	68.8	3.6	1.9	1.8
3		74.8	70.5		5.3	4.8
4			63.3			19.5
SF-12 Mental Health						
1	92.0	72.0	61.9	2.4	1.6	29.5
2	78.2	65.0	64.3	17.5	3.9	4.4
3		74.7	70.2		41.6	1.6
4			64.5			30.0