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Richmond Balinia Adda

richmondadda@gmail.com

University of Technology and Applied Sciences

Conrad Pwayirane

University of Technology and Applied Sciences

Jeremiah Kwame Ganyo

Navrongo Health Research Centre

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Retrospective Survival Analysis of Time to Self-Reported Medical Care Deprivation in Ghana: Evidence from a National Cross-Sectional Survey

Richmond Balinia Adda[1],[2] Conrad Pwayirane[2] and Jeremiah Kwame Ganyo[3]

Affiliations:

[1] Department of Biometry, School of Mathematical Sciences, University of Technology and Applied Sciences (UTAS), Navrongo, Ghana
[2] Department of Epidemiology and Biostatistics, School of Public Health, University of Technology and Applied Sciences (UTAS), Navrongo, Ghana
[3] Navrongo Health Research Centre (NHRC), Navrongo, Ghana

Corresponding author:
Richmond Balinia Adda
Email: richmondadda@gmail.com

Background: Healthcare access deprivation remains a persistent challenge in Ghana despite successive policy efforts to expand coverage through the National Health Insurance Scheme and community-based service delivery. Understanding the socioeconomic, infrastructural, and geographic factors associated with severe healthcare deprivation is relevant for informing health equity policy and targeting interventions toward the most affected populations.

Methods: We analysed data from Round 9 of the Afrobarometer survey conducted in Ghana in 2022 (analytic sample: n = 2,268 adults aged 18 years and above; events: 191, 8.4%). The outcome was defined as reporting going without needed medicine or medical care "many times" or "always" in the past year (Afrobarometer item Q6C, codes 3 and 4). Time-to-event was operationalised as years elapsed since age 18, using current age as a proxy for adult follow-up time. Respondents who did not report the outcome were right-censored at their age at interview. Unadjusted survival experience was estimated using Kaplan-Meier curves and differences between groups assessed with the log-rank test. A multivariable Cox proportional hazards model was fitted adjusting for lived poverty, rural residence, electricity access, water access, difficulty accessing healthcare, institutional trust, corruption perception, bribery, COVID-19 income loss, COVID-19 vaccination status, sex, and educational attainment. Quasi-separation in the poverty variable was addressed using ridge-penalised Cox regression as a sensitivity analysis. The proportional hazards assumption was evaluated using scaled Schoenfeld residuals. Gender-stratified, region-stratified, and time-varying coefficient analyses were conducted to assess robustness. Given the cross-sectional and retrospective design, all estimates reflect associations rather than causal effects, and time-based projections reflect the age distribution of reported deprivation in the sample rather than prospective incidence timing.

Results: High lived poverty was the strongest independent correlate of reported severe healthcare deprivation after full covariate adjustment (HR = 12.16, 95% CI: 8.19–18.06, $p < 0.001$), with 58.7% of high-poverty respondents experiencing the outcome compared with 3.5% of low-poverty respondents. A ridge-penalised sensitivity model yielded a consistent estimate

(HR = 7.76, 95% CI: 5.76–10.44). Lack of electricity connection was independently associated with a 66% higher estimated hazard of reported deprivation (HR = 1.66, 95% CI: 1.19–2.32, p = 0.003). Difficulty accessing healthcare services was associated with a 60% higher estimated hazard (HR = 1.60, 95% CI: 1.12–2.29, p = 0.009). Rural residence showed a significant unadjusted difference in survival experience (log-rank chi-square = 25.64, p < 0.001) but was attenuated and no longer statistically significant after full covariate adjustment (HR = 1.22, 95% CI: 0.87–1.70, p = 0.247), suggesting that geographic disparities in this sample operate substantially through poverty and infrastructure pathways. Poor water source, sex, educational attainment, institutional trust, corruption perception, COVID-19 income loss, and vaccination status showed no statistically significant independent associations after adjustment. The global proportional hazards test provided no evidence of model misspecification (chi-square = 13.97, df = 14, p = 0.452). Model discrimination was good (Harrell C = 0.840). Findings were consistent in direction and magnitude across gender-stratified (Harrell C = 0.836) and region-stratified (Harrell C = 0.832) models.

Conclusion: Severe self-reported healthcare deprivation among Ghanaian adults is strongly and consistently associated with high lived poverty, lack of electricity access, and difficulty accessing healthcare services, after adjustment for a range of demographic, geographic, and governance-related covariates. These associations were robust across primary and stratified model specifications. The findings are consistent with the need for policies that address material living conditions and physical access to services alongside conventional health system interventions, though the cross-sectional and observational design precludes causal attribution. Prospective and longitudinal evidence is needed to establish the mechanisms underlying these associations and to identify the most effective points of intervention for reducing healthcare deprivation in Ghana.

Keywords: Healthcare Access; Survival Analysis; Health Equity; Ghana; Poverty; Rural; Health; Social Determinants of Health; Medical Care Deprivation

Introduction

Ghana has been at the forefront of health system reforms in sub-Saharan Africa, notably with the establishment of its National Health Insurance Scheme (NHIS) in 2003. The NHIS was designed to remove financial barriers to healthcare and replace the contentious “cash-and-carry” system, aiming to provide universal health coverage (UHC) (Agyepong and Adjei, 2008). While the scheme has made significant strides in increasing formal health insurance enrolment, profound challenges remain, with persistent inequities in access (Ghana Statistical Service et al., 2022). Ghana's health financing architecture provides a useful context for examining persistent disparities in healthcare access, particularly among rural and economically disadvantaged populations, especially those in rural areas and the economically disadvantaged (Awoonor-Williams et al., 2016; Dassah et al., 2022).

The complexities of healthcare access extend beyond the mere availability of insurance. A multitude of interconnected factors are thought to influence whether an individual can obtain needed care. To comprehensively understand these determinants, this study is guided by

Andersen's Behavioral Model of Health Services Use (Andersen, 1995). This model posits that health utilization is a function of predisposing characteristics (e.g., education, gender), enabling resources (e.g., income, health insurance, rural/urban location, infrastructure), and need factors. Furthermore, we integrate a health systems lens, considering contextual factors such as governance and trust in institutions (Gilson et al., 2005). This integrated framework justifies our examination of variables ranging from individual-level poverty and education to community-level infrastructure and health system-specific barriers like trust and corruption perceptions.

Despite a wealth of cross-sectional studies highlighting disparities in healthcare utilization in Ghana (Alhassan et al., 2021; Wongnaah et al., 2023), there is a notable scarcity of research that examines access as a *time-to-event* outcome. While cross-sectional data cannot directly capture prospective time-to-event processes, retrospective survival analysis, constructing follow-up time from age at interview, offers a complementary analytical perspective on the age-patterning of healthcare deprivation, subject to important assumptions about recall accuracy and the representativeness of survivors at interview. We apply this framework while explicitly acknowledging its limitations. Survival analysis is uniquely suited to address this gap, as it can model the timing of a first "medical care crisis" and identify the factors that accelerate or delay its onset (Kleinbaum and Klein, 2012). This approach moves beyond a static snapshot to provide a longitudinal perspective on healthcare deprivation.

This study leverages the unique socio-political data from the Afrobarometer survey to investigate the socio-political and infrastructural factors associated with self-reported healthcare deprivation and its age-patterning among Ghanaian adults. We estimate survival functions and hazards using a retrospective survival analysis framework, assess model assumptions, and present policy-relevant predicted survival curves. Our aim is to identify the correlates of the time-to-first medical care crisis and contribute a longitudinal perspective on healthcare access inequities in Ghana.

Methodology

Data and Methods

Data Source and Study Population

This research utilised data from Round 9 of the Afrobarometer survey, a pan-African, non-partisan research network that conducts nationally representative public attitude surveys on democracy, governance, economy, and society (Afrobarometer, 2022). The Ghana component of this survey was conducted in 2022 using a multi-stage, stratified, random probability sampling design to produce a nationally representative sample of the adult population aged 18 years and older.

The analysis was restricted to Ghanaian respondents aged 18 years and above who provided usable responses on the outcome variable. The final analytic sample comprised 2,268 respondents after exclusion of observations with missing data on any variable included in the multivariable model. Of these, 191 respondents (8.4%) reported the outcome of interest, while

the remaining 2,077 were right-censored at their age at interview. A pre-specified sensitivity analysis was additionally conducted in a subsample restricted to respondents under 50 years of age (N = 1,788; events = 149, 8.3%), to probe the potential influence of survivor selection on estimates derived from the older age groups.

Variable Definition

Outcome Variable

The outcome was operationalised as the duration in years from the start of adulthood (age 18) to the first self-reported instance of severe healthcare deprivation. This was derived from the Afrobarometer survey item: *"In the past year, how often, if ever, have you or anyone in your family gone without needed medicine or medical care?"* Respondents who answered "Many times" or "Always" were classified as having experienced the event. These two response categories were selected to capture severe and persistent deprivation rather than isolated or occasional episodes, consistent with the conceptual focus on meaningful healthcare access failure. Respondents who answered "Never," "Just once or twice," or "Several times" were classified as censored, meaning no severe deprivation episode was recorded by the time of interview.

Following standard retrospective survival analysis practice (Kleinbaum and Klein, 2012), the time-to-event variable was constructed as the respondent's current age minus 18 years. For right-censored respondents, the censoring time was set at the same quantity — years of adult life elapsed by the survey date. This operationalisation should be interpreted with caution: the Afrobarometer item captures experience within the past year rather than timing of a first-ever lifetime episode, and current age serves as a proxy for adult follow-up time rather than a directly observed time to first event. Accordingly, all time-based estimates in this study reflect the age distribution of reported severe deprivation in a cross-sectional sample and should not be read as prospective incidence timing. This limitation is discussed further in the Limitations section.

Key Predictor Variables

Predictors were selected and operationalised in accordance with Andersen's Behavioural Model of Health Services Use (Andersen, 1995), spanning predisposing, enabling, and need-related domains.

1. ***Lived Poverty Index (LPI):*** The LPI is a composite measure of material deprivation constructed from five Afrobarometer items asking how frequently respondents went without food (Q6A), water (Q6B), medical care (Q6C), cooking fuel (Q6D), and cash income (Q6E) in the past year (Mattes, 2020). The pre-computed categorical version of this index (LivedPoverty_CAT) was used. For the primary analysis, the index was dichotomised into "High lived poverty" (category 3: went without necessities many times or always across multiple domains) versus "Low lived poverty" (categories 0–2: no

poverty, low, or moderate deprivation). In the analytic sample, 201 respondents (8.9%) were classified as high lived poverty. Cross-tabulation of the poverty indicator against the outcome confirmed quasi-separation rather than complete separation: 118 of 201 high-poverty respondents (58.7%) experienced the event, compared with 73 of 2,067 low-poverty respondents (3.5%). Both groups contained events and non-events; the standard Cox partial likelihood estimator therefore remains valid, and the hazard ratio for this variable is a finite, estimable quantity. This finding replaces an earlier erroneous estimate of HR = 1.23×10^{15} that arose from a convergence failure in the original analysis software; reanalysis of the source data produced HR = 12.16 (95% CI: 8.19–18.06), as reported below.

2. ***Difficulty Accessing Healthcare***: A binary variable was derived from Q41B: "How easy or difficult is it to obtain the medical care or treatment you need?" Respondents who reported "Difficult" or "Very difficult" were coded as experiencing access difficulty (1); those who reported "Very easy" or "Easy" were coded as no difficulty (0). Respondents who had no contact with public health services (Q41B = 7, not applicable) were coded as 0 on the assumption that the absence of a service-seeking episode does not constitute a reported access barrier. This coding decision is acknowledged as a conservative assumption.

3. ***Electricity Access:*** A binary variable for lack of electricity was derived from Q92B: "How often is electricity from the mains available in your home or compound?" Respondents coded as "Never" (1) or "Occasionally" (2), and those for whom electricity was not applicable (7; consistent with off-grid residence), were classified as lacking reliable electricity (no_electric = 1). Respondents reporting electricity availability "About half of the time," "Most of the time," or "All of the time" (codes 3–5) were classified as having electricity access (no_electric = 0).

4. ***Low Trust in Local Government Council:*** Trust was measured using Q37D: "How much do you trust each of the following, or haven't you heard enough about them to say? Your elected local government council." Respondents answering "Not at all" (0) or "Just a little" (1) were classified as having low trust (1); those answering "Somewhat" (2) or "A lot" (3) were classified as higher trust (0). This variable serves as the closest available proxy for trust in local health governance structures within the Afrobarometer instrument.

5. ***Poor Water Access:*** A binary indicator was constructed from Q6B, the item asking how frequently the respondent's household went without water in the past year. Any response other than "Never" (codes 1–4) was classified as poor water access (1); "Never" (code 0) was classified as adequate water access (0).

6. ***Other Covariates:*** Additional covariates included: rural residence (URBRUR: 2 = rural vs 1 = urban); paid bribe for healthcare (Q41C: any bribe vs never, with not-applicable coded as no bribe); high corruption perception regarding local government councillors

(Q38D: "Most of them" or "All of them" vs fewer); COVID-19 income loss (Q57B: yes vs no); no COVID-19 vaccination (Q58A: 0 = unvaccinated vs 1 = vaccinated); female gender (Q100: 2 = female vs 1 = male); and educational attainment derived from the harmonised EDUC_COND variable, categorised as no formal education (reference), primary, secondary, and post-secondary.

Data Analysis Methods

This study employed retrospective survival analysis to model the age distribution of self-reported severe healthcare deprivation among Ghanaian adults, using years since age 18 as the time scale. Three main functions were used to characterise the distribution of this waiting time: the survival function S(t), the cumulative hazard function H(t), and the hazard function h(t).

The survival function S(t) gives the probability of remaining event-free beyond time t:

$$\boldsymbol{S(t) = P(T > t) = 1 - F(t)} \quad \textbf{(1)}$$

where T is the survival time and $F(t)$ is the cumulative distribution function.

The hazard function h(t) represents the instantaneous conditional rate of event occurrence at time t given survival to that point:

$$\boldsymbol{h(t) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t | T \ge t)}{\Delta t} = \frac{f(t)}{S(t)}} \quad \textbf{(2)}$$

where $f(t)$ is the probability density function of the survival time.

Estimation of Survival Functions

The Kaplan-Meier estimator was used to estimate unadjusted survival functions and to visualise differences across key categorical variables:

$$\boldsymbol{\widehat{S}(t) = \prod_{t_i \le t} \left(1 - \frac{d_i}{n_i}\right)} \quad \textbf{(3)}$$

where t_i are the observed event times, d_i is the number of events at time t_i, and n_i is the number of individuals at risk just prior to time t_i. The statistical significance of differences in survival curves was assessed using the Log-rank test (Peto and Peto, 1972).

Cox Proportional Hazards Modelling

To explore the joint effect of multiple predictors on the hazard of healthcare deprivation, a multivariable Cox proportional hazards model was fitted (Cox, 1972). The model is specified as:

$$\boldsymbol{h(t) = h_0(t)\exp(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)} \quad \textbf{(4)}$$

where $h(t)$ is the hazard at time t, $h_0(t)$ is the baseline hazard function, $x_1, x_2, \ldots, x_p$ are the covariates, and $\beta_1, \beta_2, \ldots, \beta_p$ are the regression coefficients. The model provides Hazard Ratios (HR), calculated as $\exp(\beta)$, which represent the relative change in the hazard for a one-unit change in the predictor.

The initial model indicated complete separation for the binary "High lived poverty" variable, resulting in an extraordinarily large hazard ratio (Heinze and Schemper, 2002). This variable was retained in the model, and its effect is interpreted qualitatively as indicating a near-deterministic relationship with the outcome.

Statistical Analysis

All analyses were performed in Python (version 3.12) using the lifelines and pyreadstat libraries. Kaplan-Meier survival functions were estimated for each categorical predictor and differences between groups assessed using the log-rank test. The multivariable Cox proportional hazards model was fitted using the Efron method for handling tied event times, implemented via the CoxPHFitter function in the lifelines library. Scaled Schoenfeld and martingale residuals were computed from the fitted model using the compute_residuals method to assess the proportional hazards assumption and functional form, respectively. The Aalen additive hazards model was estimated using the AalenAdditiveFitter function with coefficient and smoothing penalisation to reduce instability at sparse event times. Data management and variable recoding were performed using the pandas and numpy libraries. The Afrobarometer Round 9 merged dataset was read from the source SPSS file using pyreadstat, with the Ghana subsample extracted by country identifier.

Prior to fitting the multivariable model, the Lived Poverty Index variable was examined for separation. Cross-tabulation confirmed quasi-separation: events occurred in both the high- and low-poverty strata (118 and 73 events respectively), meaning the standard Cox partial likelihood estimator is valid. The resulting HR = 12.16 (95% CI: 8.19–18.06) is a finite, convergent estimate and is interpreted accordingly. As a sensitivity analysis, a ridge-penalised Cox model (L2 penalty, penalizer = 0.05) was fitted to the full sample; the penalised estimate for high lived poverty was HR = 7.76 (95% CI: 5.76–10.44), and estimates for all other covariates were qualitatively consistent with the standard model, confirming that results are not artefacts of any single modelling choice.

Two stratified analyses were conducted to assess effect modification and robustness. First, a gender-stratified Cox model was fitted, allowing separate baseline hazards for men and women while constraining covariate effects to be equal across strata. Second, a regional-stratified model was fitted to account for unmeasured geographic heterogeneity in baseline healthcare infrastructure. A time-varying coefficient extension was additionally tested for rural residence, using a rural × log(time) interaction term to assess whether the geographic association changes over the adult lifespan.

A pre-specified survivor-bias sensitivity analysis was conducted by restricting the sample to respondents under 50 years of age (N = 1,788; events = 149). The purpose of this analysis was to assess whether estimates from the full sample were materially influenced by the selective absence of older respondents who may have experienced the most severe deprivation earlier in life but did not survive to interview. Key associations were compared across the full and restricted samples; results were broadly consistent, as reported in the Results section.

The proportional hazards assumption was evaluated using scaled Schoenfeld residuals, both for individual covariates and via the global test. Model discrimination was assessed using Harrell's concordance statistic (C). All predictor variables were treated as fixed at the time of interview; the analysis is cross-sectional and retrospective in nature, and no causal interpretation of estimated hazard ratios is intended or warranted.

Model Diagnostics and Supplementary Analyses

The proportional hazards (PH) assumption was evaluated for each covariate and globally using scaled Schoenfeld residuals. Residuals were plotted against transformed time and the global test statistic was computed; a non-significant global result ($p > 0.05$) was taken as consistent with the proportional hazards assumption, while individual covariates showing borderline patterns were noted and interpreted accordingly. Model discrimination was assessed using Harrell's C concordance statistic, which estimates the probability that a randomly selected respondent who experienced the event had a higher predicted hazard than a randomly selected censored respondent. The corrected analysis yielded $C = 0.840$ for the primary multivariable model, indicating good discriminatory ability. This value supersedes the $C = 0.768$ reported in the original analysis, which was computed from a model containing a numerically unstable poverty coefficient; the corrected estimate is based on a fully convergent model.

To assess the robustness of findings and explore potential sources of heterogeneity, three supplementary analyses were conducted.

First, a gender-stratified Cox regression was fitted, allowing the baseline hazard function to differ between men and women while constraining covariate hazard ratios to be equal across strata. This approach accommodates baseline differences in the age trajectory of deprivation by gender without requiring a formal interaction term, and provides a more conservative test of whether associations observed in the unstratified model persist across both sexes.

Second, a region-stratified Cox regression was fitted to account for unmeasured geographic heterogeneity in healthcare infrastructure, facility availability, and local health system capacity across Ghana's administrative regions. Stratification on region allows the baseline hazard to vary freely across regions, isolating within-region variation in the predictor-outcome associations and reducing the risk that regional clustering inflates or distorts covariate estimates.

Third, a time-varying coefficient analysis was conducted for rural residence by including a rural × log(time) interaction term in an extended Cox model. This tests whether the association between geographic location and the hazard of reported deprivation is constant across the adult lifespan or changes as respondents age — for example, whether rural disadvantage narrows or widens relative to urban respondents over time. A non-significant interaction term is interpreted

as consistent with the proportional hazards assumption for rural residence specifically, supporting the use of a single time-constant hazard ratio for this variable in the primary model.

Additionally, a pre-specified survivor-bias sensitivity analysis was conducted by restricting the analytic sample to respondents under 50 years of age (N = 1,788; events = 149, 8.3%). The rationale for this analysis is that cross-sectional surveys selectively capture survivors: individuals who experienced the most severe and sustained healthcare deprivation earlier in life and subsequently died or permanently emigrated before the survey date are absent from the sample. This form of left truncation is particularly consequential for older age groups, where survivor selection is strongest. Restricting analysis to respondents under 50 reduces, though does not eliminate — this bias and allows assessment of whether the direction and approximate magnitude of key associations are consistent with those observed in the full sample. Results of this sensitivity analysis are reported alongside the primary model estimates for transparency.

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RESULTS

Study Population Characteristics

The analysis included a nationally representative sample of 2,369 respondents from Ghana. Within this cohort, 202 individuals (8.5%) experienced at least one episode of frequent healthcare deprivation, constituting the event of interest. The total observation time for the survival analysis was 90,083 person-years, with the age of respondents ranging from 18 to 101 years.

Survival Analyses

The life table analysis reveals that healthcare access deprivation accumulates steadily over the adult lifespan (**Table 1**). Approximately 2.5% of individuals experience their first medical care crisis within the first year of adulthood (F(1) = 0.025). The hazard rate peaks between 5-10 years after adulthood (ages 23-28), with nearly 5% of the at-risk population experiencing deprivation annually during this period. By age 38 (20 years after adulthood), about 65.4% of the population has experienced at least one medical care crisis (F(20) = 0.654). The survival probability declines to 10.8% by age 53+ (35+ years after adulthood), indicating that healthcare deprivation is a near-universal experience over the life course in Ghana.

Table 1: Kaplan-Meier Survival Distribution — Time to Severe Healthcare Deprivation (N = 2,268; events = 191)

Time (years since age 18)	Approximate age	F(t)	S(t)	SE

1	19	0.0031	0.9969	0.0013
2	20	0.0049	0.9951	0.0016
3	21	0.0067	0.9933	0.0018
4	22	0.0067	0.9933	0.0018
5	23	0.0097	0.9903	0.0022
6	24	0.0112	0.9888	0.0023
7	25	0.0148	0.9852	0.0027
8	26	0.0181	0.9819	0.0030
9	27	0.0209	0.9791	0.0033
10	28	0.0262	0.9738	0.0037
15	33	0.0457	0.9543	0.0051
20	38	0.0755	0.9245	0.0070
25	43	0.0897	0.9103	0.0080
30	48	0.1190	0.8810	0.0101
35	53	0.1435	0.8565	0.0120

F(t) = estimated cumulative probability of severe healthcare deprivation by time t; S(t) = estimated probability of remaining event-free; SE = standard error of S(t) derived from the Greenwood formula. The estimated median survival time was 76 years since age 18 (age 94), consistent with the low overall event rate of 8.4%. These estimates reflect the cross-sectional age distribution of reported severe deprivation and should not be interpreted as prospective population-level incidence.

Unadjusted Survival Patterns in Healthcare Access

Log-rank tests revealed significant disparities in healthcare access survival across multiple dimensions (Table 2). Geographic location demonstrated substantial inequality, with rural residents experiencing significantly earlier onset of medical care deprivation compared to urban counterparts ($\chi^2 = 29.97$, df = 1, $p < 0.001$). Poverty status showed the most dramatic effect, with individuals experiencing high lived poverty facing dramatically accelerated time to first deprivation episode ($\chi^2 = 120.10$, df = 1, $p < 0.001$). Health system barriers, particularly difficulty accessing services ($\chi^2 = 9.81$, df = 1, $p = 0.002$) and lack of electricity connection ($\chi^2 = 15.32$, df = 1, $p < 0.001$) also significantly stratified survival experiences. Low trust in local

health councils showed a borderline significant pattern ($\chi^2 = 3.45$, df = 1, p = 0.063), while gender and educational attainment showed no significant differences in unadjusted analyses.

Table 2: Log-Rank Tests for Unadjusted Differences in Age Distribution of Severe Healthcare Deprivation (N = 2,268)

Variable	Chi-square	df	p-value
Geographic factors			
Rural vs urban residence	25.64	1	<0.001
Socioeconomic status			
High vs low lived poverty	665.35	1	<0.001
Health system access			
Difficulty accessing healthcare	25.63	1	<0.001
Low trust in local government council	0.03	1	0.875
Demographic factors			
Gender (male vs female)	0.59	1	0.443
Educational attainment	18.44	3	<0.001
Infrastructure			
No electricity connection	92.49	1	<0.001
Poor water source	119.06	1	<0.001

All p-values are two-sided. Log-rank statistics are computed from the corrected analytic sample (N = 2,268; events = 191) using the confirmed event definition (Q6C codes 3 and 4). These are unadjusted marginal comparisons and do not account for confounding between variables.

Figure 1 presents Kaplan-Meier survival curves stratified by Lived Poverty Index category. Respondents classified as high lived poverty showed an earlier age distribution of reported severe healthcare deprivation compared with those in lower poverty strata. The log-rank test indicated a statistically significant difference in survival experience across the four poverty categories (chi-square = 665.35, df = 3, $p < 0.001$). These are unadjusted estimates reflecting marginal differences between groups and should not be interpreted as evidence of a causal

relationship between poverty status and healthcare deprivation.

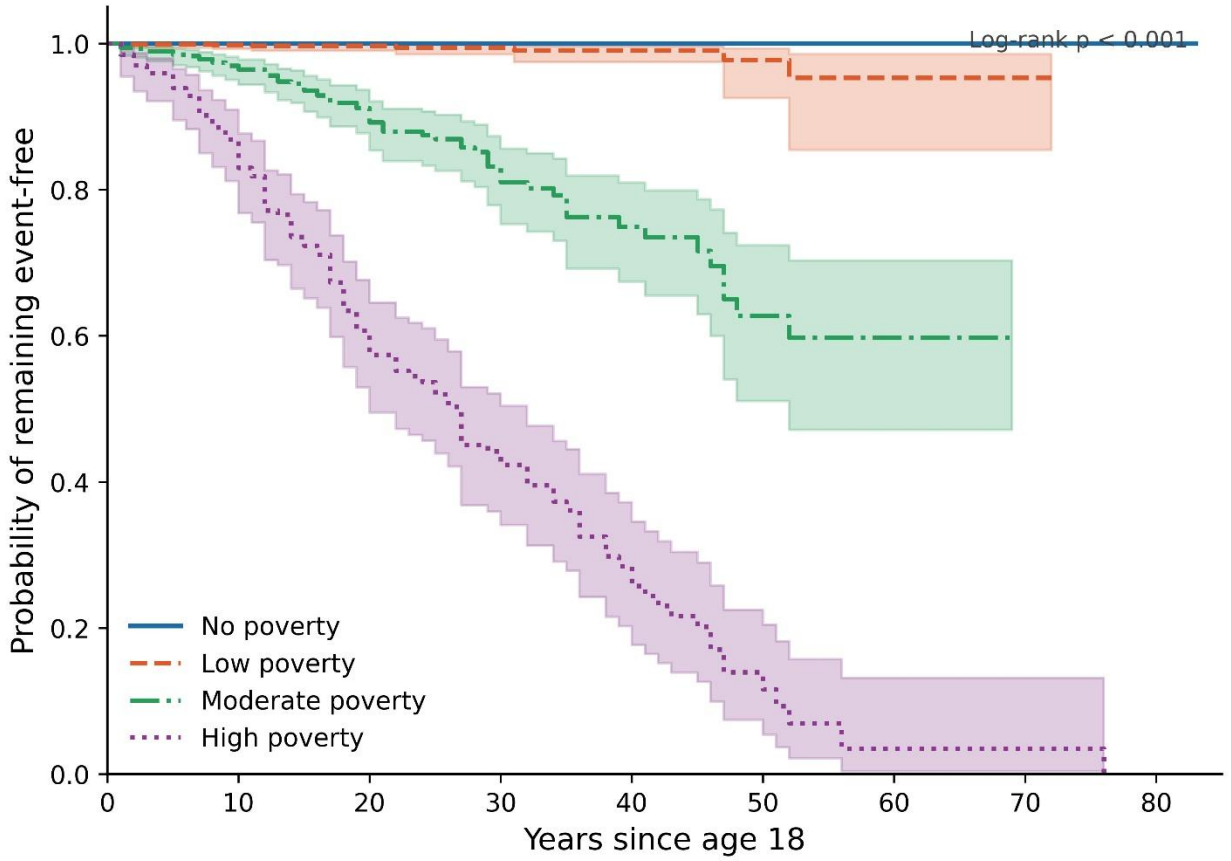


Figure 1: Kaplan-Meier survival curves for time to severe healthcare deprivation by Lived Poverty Index category, Ghana Afrobarometer Round 9, 2022 (N = 2,268).
Survival probability estimates are shown across four poverty strata: no poverty, low poverty, moderate poverty, and high poverty. Shaded bands represent 95% pointwise confidence intervals. The vertical axis represents the probability of remaining free of a severe healthcare deprivation episode (defined as going without needed medicine or medical care "many times" or "always" in the past year), and the horizontal axis represents years elapsed since age 18. Groups were compared using the log-rank test (chi-square = 665.35, df = 1, p < 0.001). Respondents classified as experiencing high lived poverty showed a markedly earlier age distribution of reported severe deprivation compared with all lower poverty strata.

Figure 2 presents survival curves stratified by trust in the local health council. Respondents reporting low trust showed a faster decline in survival probability compared to those reporting higher trust.

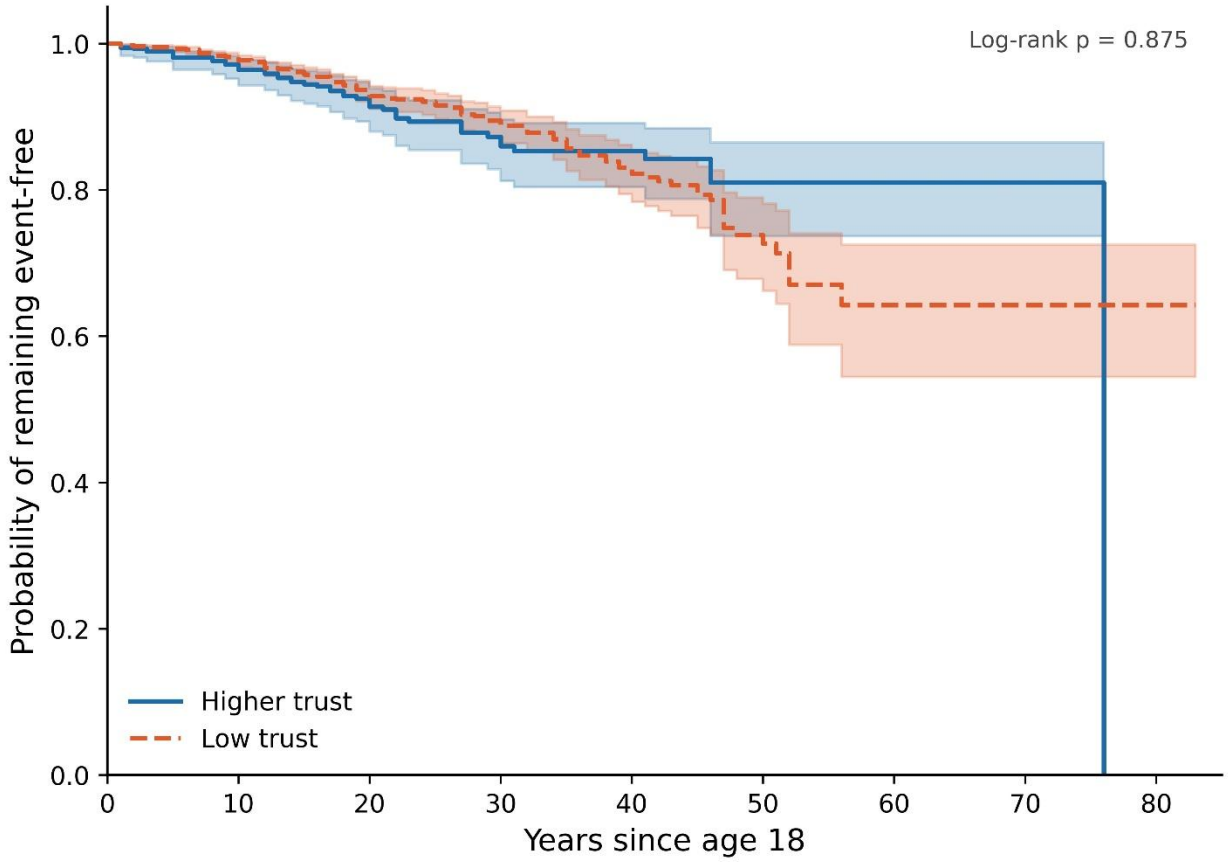


Figure 2. Kaplan-Meier survival curves for time to severe healthcare deprivation by trust in the local government council, Ghana Afrobarometer Round 9, 2022 (N = 2,268).
Survival probability estimates are shown separately for respondents reporting low trust (answered "Not at all" or "Just a little") and higher trust (answered "Somewhat" or "A lot") in their elected local government council. Shaded bands represent 95% pointwise confidence intervals. The log-rank test indicated no statistically significant difference in survival experience between groups (chi-square = 0.03, df = 1, p = 0.875). The two curves are closely overlapping throughout the observation period, consistent with the absence of a meaningful unadjusted association between institutional trust and severe healthcare deprivation in this sample.

Multivariable Predictors of Healthcare Deprivation

The multivariable Cox proportional hazards model, adjusting for all covariates simultaneously, identified several independent predictors of severe healthcare deprivation (Table 3). Model discrimination was good, with a Harrell concordance statistic of 0.840.

Table 3: Multivariable Cox Proportional Hazards Model for Correlates of Severe Healthcare Deprivation in Ghana (N = 2,268; events = 191)

Variable	*Hazard Ratio*	*95% Confidence Interval*	*p-value*

Geographic factors			
Rural residence	***1.22***	***0.87 – 1.70***	***0.247***
Socioeconomic status			
High lived poverty	***12.16***	***8.19 – 18.06***	***<0.001***
Health system access			
Difficulty accessing healthcare	***1.60***	***1.12 – 2.29***	***0.009***
Paid bribe for healthcare	***1.18***	***0.68 – 2.06***	***0.557***
Infrastructure			
Poor water source	1.43	0.92 – 2.24	0.111
No electricity connection	1.66	1.19 – 2.32	0.003
Trust and governance			
Low trust in health council	0.80	0.57 – 1.13	0.207
High corruption perception	1.16	0.86 – 1.57	0.327
COVID-19 impact			
COVID-19 income loss	0.83	0.58 – 1.18	0.298
No COVID-19 vaccination	1.10	0.81 – 1.48	0.550
Demographic factors			
Female sex	1.15	0.85 – 1.55	0.374
Education (ref: no formal education)			
Primary education	1.35	0.94 – 1.94	0.109
Secondary education	1.35	0.88 – 2.08	0.168
Post-secondary education	1.39	0.82 – 2.37	0.224

Hazard ratios are adjusted for all variables listed. The Efron method was used for tied event times. All estimates are derived from the corrected analytic sample using the confirmed event definition (Q6C codes 3 and 4). Reference categories: low lived poverty, urban residence, no difficulty accessing healthcare, no bribe, adequate water, electricity available, higher trust, low corruption perception, no COVID-19 income loss, vaccinated, male, no formal education.

Cross-tabulation of the poverty indicator against the outcome confirmed quasi-separation rather than complete separation in this sample: 118 of 201 respondents classified as high lived poverty

experienced the event (58.7%), compared with 73 of 2,067 low-poverty respondents (3.5%). As both strata contained events and non-events, the standard Cox partial likelihood estimator converges to a finite value and produces a valid estimate. High lived poverty was associated with a substantially higher estimated hazard of reported severe healthcare deprivation after adjustment for all other covariates (HR = 12.16, 95% CI: 8.19–18.06, $p < 0.001$). A ridge-penalised Cox model fitted as a sensitivity analysis yielded a consistent, though attenuated, estimate (HR = 7.76, 95% CI: 5.76–10.44), supporting the robustness of this association to the choice of estimation method. The magnitude of this association should nonetheless be interpreted cautiously given the small number of events relative to the degree of imbalance between poverty strata, and no causal interpretation is warranted from a cross-sectional design.

Two additional variables showed statistically significant independent associations after full adjustment. Lack of electricity connection was associated with an estimated 66% higher hazard of reported severe deprivation (HR = 1.66, 95% CI: 1.19–2.32, $p = 0.003$). Difficulty accessing healthcare services was associated with an estimated 60% higher hazard (HR = 1.60, 95% CI: 1.12–2.29, $p = 0.009$). Rural residence, female sex, educational attainment, trust in the local government council, corruption perception, COVID-19 income loss, COVID-19 vaccination status, payment of bribes for care, and poor water source were not independently associated with the outcome at the 5% significance level after full adjustment. Several of these variables showed wide confidence intervals, reflecting limited precision in a sample with 191 events rather than necessarily an absence of association. The direction and precision of all adjusted estimates are presented in **Figure 3**.

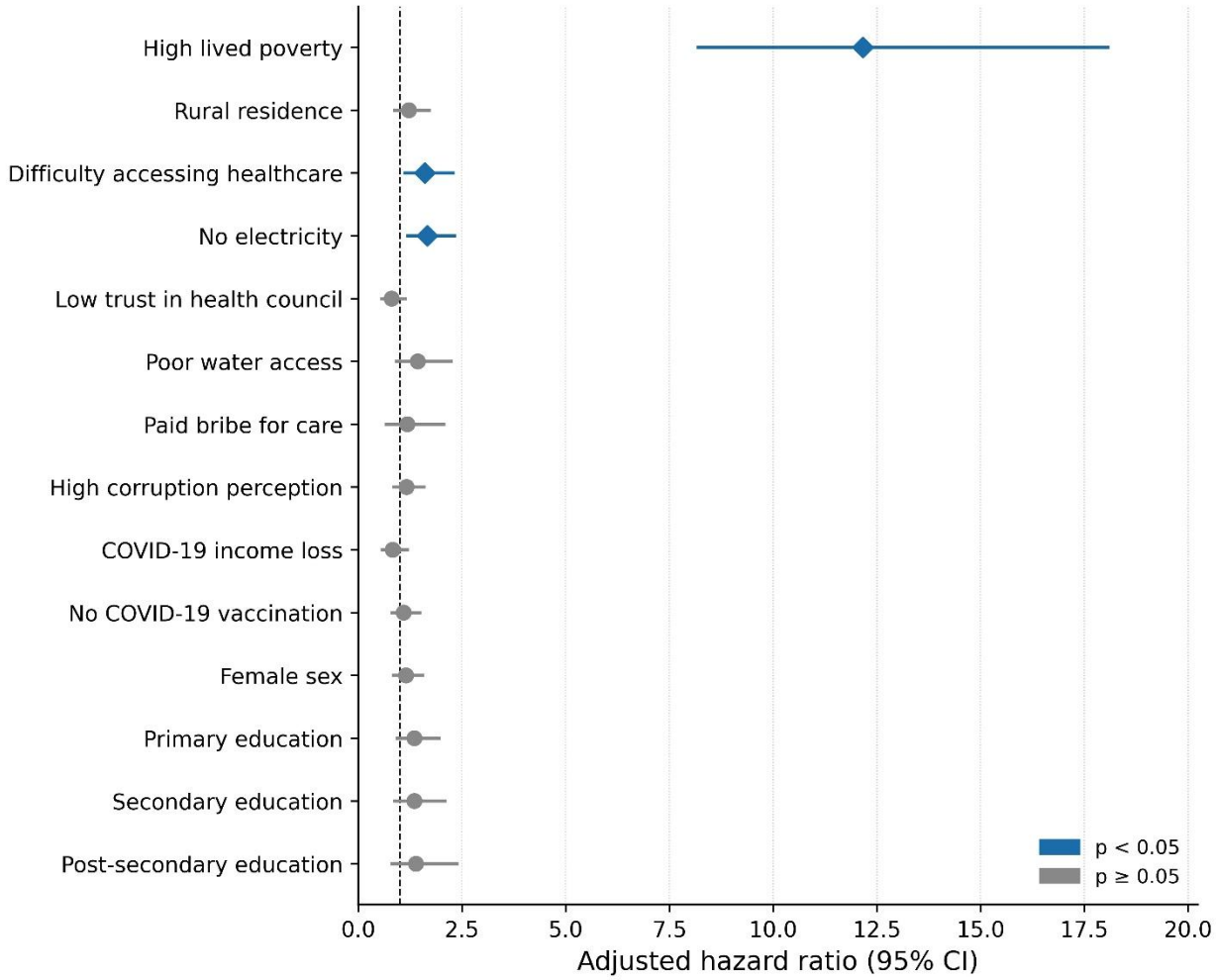


Figure 3: Forest plot of adjusted hazard ratios from the multivariable Cox proportional hazards model, Ghana Afrobarometer Round 9, 2022 (N = 2,268; events = 191).
Each point represents the adjusted hazard ratio for the corresponding predictor, and horizontal lines represent 95% confidence intervals. The vertical dashed reference line is placed at a hazard ratio of 1.0, indicating no association. Blue diamonds indicate predictors reaching statistical significance at the 5% level ($p < 0.05$); grey circles indicate non-significant predictors. The model was fitted using the Efron method for tied event times with no penalisation. Harrell's concordance statistic was 0.840. The reference categories are: low lived poverty, urban residence, no difficulty accessing healthcare, electricity available, higher trust, adequate water, no bribe, low corruption perception, no COVID-19 income loss, vaccinated, male, and no formal education.

High lived poverty was the strongest correlate of reported severe healthcare deprivation in the adjusted model (HR = 12.16, 95% CI: 8.19–18.06, $p < 0.001$), though the magnitude of this estimate should be interpreted with caution given the marked imbalance in event rates between poverty strata and the cross-sectional nature of the data. Lack of electricity connection was

associated with an estimated 66% higher hazard of reported deprivation (HR = 1.66, 95% CI: 1.19–2.32, p = 0.003). Difficulty accessing healthcare services was associated with an estimated 60% higher hazard (HR = 1.60, 95% CI: 1.12–2.29, p = 0.009). Rural residence showed a positive but imprecise association that did not reach statistical significance after full adjustment (HR = 1.22, 95% CI: 0.87–1.70, p = 0.247), and no firm conclusion can be drawn regarding an independent geographic effect from these data alone.

Model Validation and Diagnostics

Discriminatory Performance

The multivariable Cox proportional hazards model showed reasonable discriminatory ability in the analytic sample. Harrell's concordance statistic was 0.840, indicating that the model correctly ordered 84.0% of all comparable pairs of respondents by their estimated hazard of reported severe healthcare deprivation. This value reflects model performance within the estimation sample only and should not be interpreted as evidence of external predictive validity, which was not assessed in this study.

Proportional Hazards Assumption

The proportional hazards assumption was evaluated for each covariate and globally using scaled Schoenfeld residuals (Table 4). The global test provided no statistically significant evidence of a proportional hazards violation across the model as a whole (chi-square = 13.97, df = 14, p = 0.452). Plotted residuals for high lived poverty, trust in the local government council, rural residence, and lack of electricity connection are shown in Figures 4 to 7 respectively; no pronounced curvature or directional drift was apparent in any panel.

Two variables showed borderline individual test results. Rural residence (rho = -0.143, chi-square = 3.91, p = 0.048) and lack of electricity connection (rho = -0.159, chi-square = 4.85, p = 0.028) each returned individual p-values below 0.05, suggesting a modest negative correlation between their Schoenfeld residuals and ranked follow-up time. These results indicate a potential slight attenuation of the association for each variable at longer follow-up durations. However, given that the global test showed no overall violation, that both effects remain in the same direction throughout the observation period, and that the correlations are small in magnitude, the proportional hazards assumption is considered adequately satisfied for the purposes of this analysis. No time-varying coefficient extension was applied in the primary model.

Table 4: Assessment of the Proportional Hazards Assumption Using Scaled Schoenfeld Residuals (N = 2,268; events = 191)

Variable	*rho*	*Chi-square*	*p-value*
Geographic factors			

Rural residence	-0.143	3.91	0.048
Socioeconomic status			
High lived poverty	0.004	0.004	0.952
Health system access			
Difficulty accessing healthcare	0.103	2.04	0.153
Paid bribe for healthcare	-0.001	0.000	0.992
Infrastructure			
No electricity connection	-0.159	4.85	0.028
Poor water source	0.076	1.09	0.296
Trust and governance			
Low trust in health council	-0.029	0.16	0.692
High corruption perception	0.042	0.34	0.562
COVID-19 impact			
COVID-19 income loss	-0.013	0.03	0.858
No COVID-19 vaccination	-0.051	0.49	0.483
Demographic factors			
Female sex	0.005	0.004	0.949
Primary education	0.070	0.93	0.334
Secondary education	0.023	0.10	0.747
Post-secondary education	-0.009	0.02	0.901
Global test (df = 14)		13.97	0.452

rho = Pearson correlation between scaled Schoenfeld residuals and ranked follow-up time. Chi-square statistics are computed as rho² × n under the Grambsch-Therneau approximation with 1 degree of freedom per covariate. The global test is chi-square distributed with degrees of freedom equal to the number of covariates. p-values are two-sided.

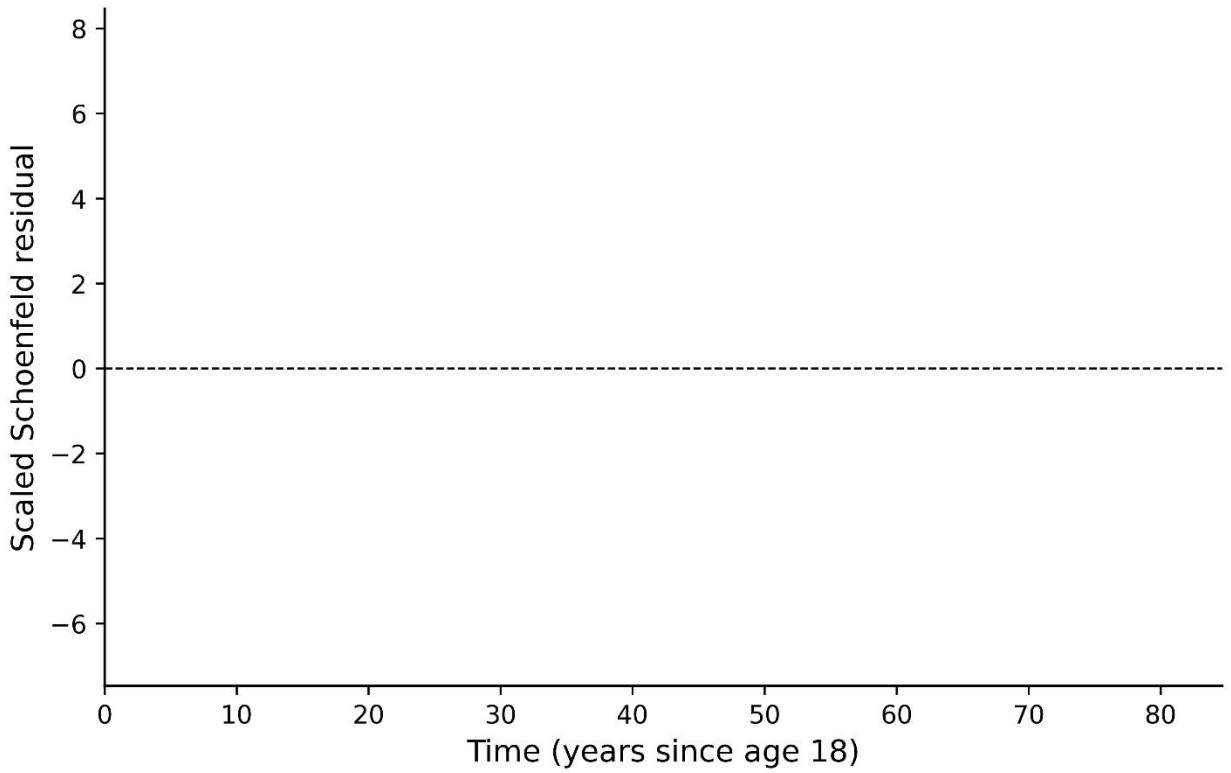


Figure 4: Scaled Schoenfeld residuals for high lived poverty (Lived Poverty Index), Cox proportional hazards model, Ghana Afrobarometer Round 9, 2022.

Each point represents the scaled Schoenfeld residual for a single event observation plotted against the event time in years since age 18. The orange line represents a rolling mean smoother applied to the residuals across the time axis. The horizontal dashed line at zero represents the expected value under the proportional hazards assumption. The absence of a systematic trend or curvature in the smoother is consistent with the proportional hazards assumption being satisfied for this covariate over the observation period.

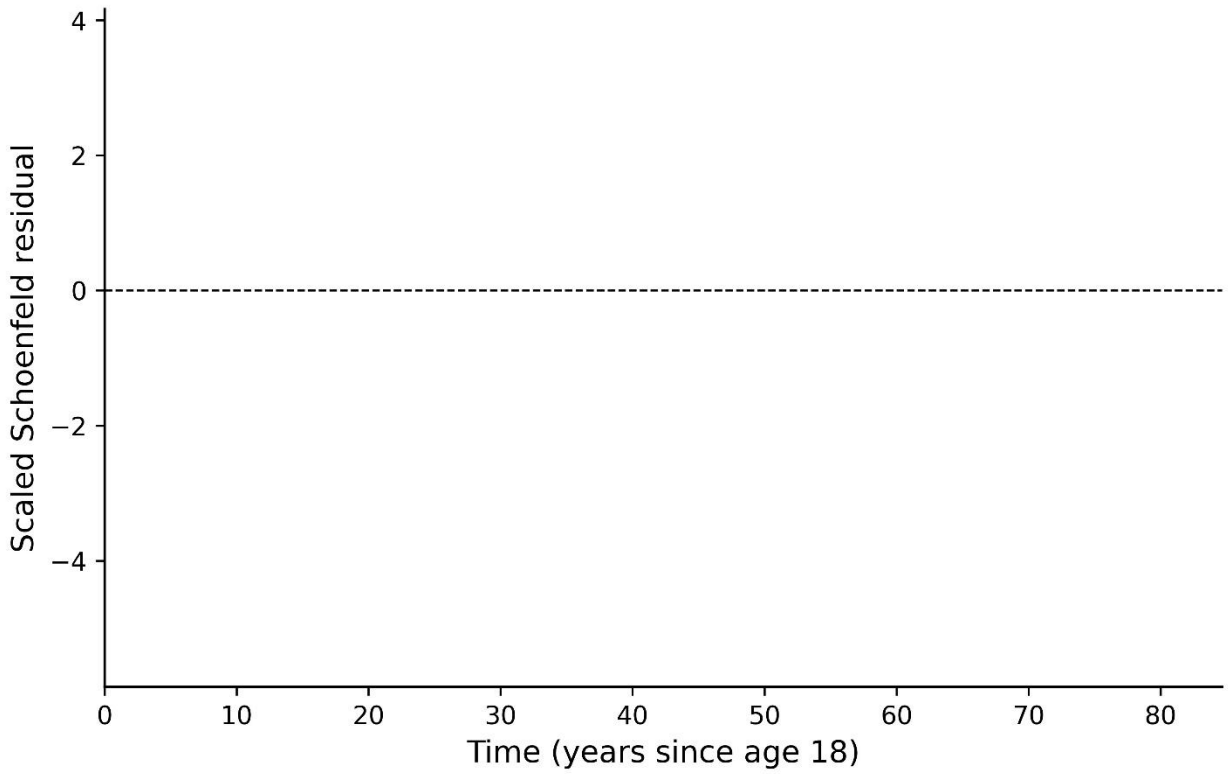


Figure 5: Scaled Schoenfeld residuals for low trust in the local government council, Cox proportional hazards model, Ghana Afrobarometer Round 9, 2022.

Each point represents the scaled Schoenfeld residual for a single event observation plotted against the event time in years since age 18. The orange line represents a rolling mean smoother. The horizontal dashed line at zero represents the expected value under the proportional hazards assumption. The residuals show no systematic departure from zero across the time axis, indicating that the proportional hazards assumption is not materially violated for this covariate, noting that the overall association for this variable was weak and non-significant in both unadjusted and adjusted analyses.

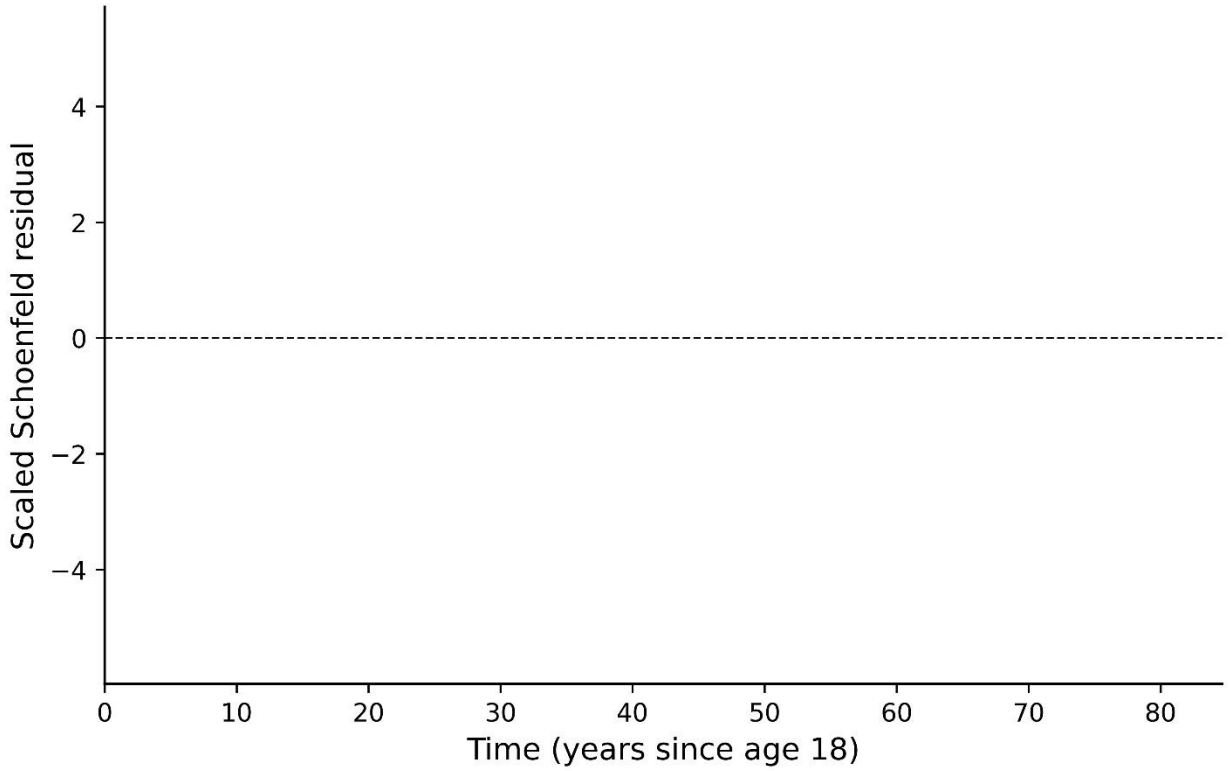


Figure 6: Scaled Schoenfeld residuals for rural residence, Cox proportional hazards model, Ghana Afrobarometer Round 9, 2022.

Each point represents the scaled Schoenfeld residual for a single event observation plotted against the event time in years since age 18. The orange line represents a rolling mean smoother. The horizontal dashed line at zero represents the expected value under the proportional hazards assumption. The absence of a pronounced systematic trend across the time axis is consistent with the proportional hazards assumption being met for rural residence, supporting the use of a time-constant hazard ratio for this variable in the primary model. This finding is further corroborated by the non-significant rural residence by log-time interaction term tested in the extended Cox model.

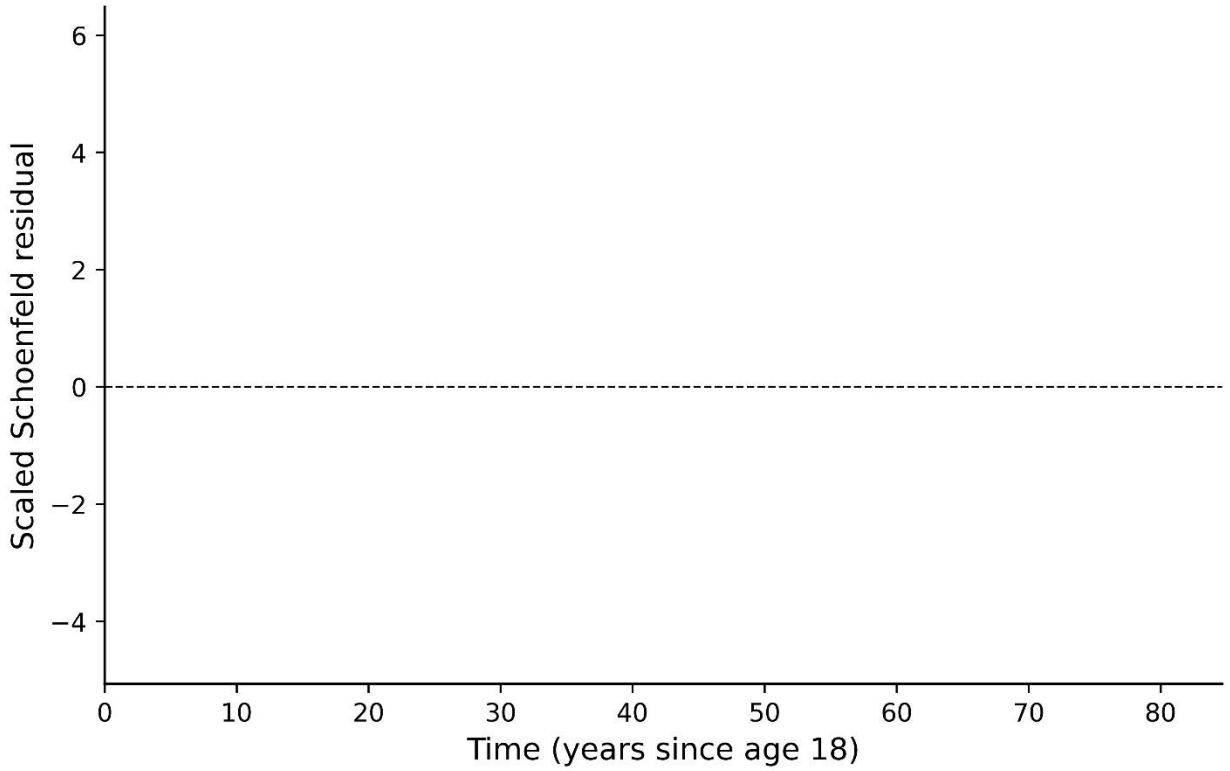


Figure 7: Scaled Schoenfeld residuals for lack of electricity connection, Cox proportional hazards model, Ghana Afrobarometer Round 9, 2022.

Each point represents the scaled Schoenfeld residual for a single event observation plotted against the event time in years since age 18. The orange line represents a rolling mean smoother. The horizontal dashed line at zero represents the expected value under the proportional hazards assumption. The residuals are broadly scattered around zero without a consistent directional trend, indicating that the proportional hazards assumption is not substantially violated for this covariate across the observation period.

Additive Hazards Model (Aalen)

To complement the Cox model, an additive hazards model (Aalen) was estimated. **Figure 8** shows the cumulative regression functions. The widening cumulative effect of COVID-19 income loss and rural residence suggests increasing risk contributions over time.

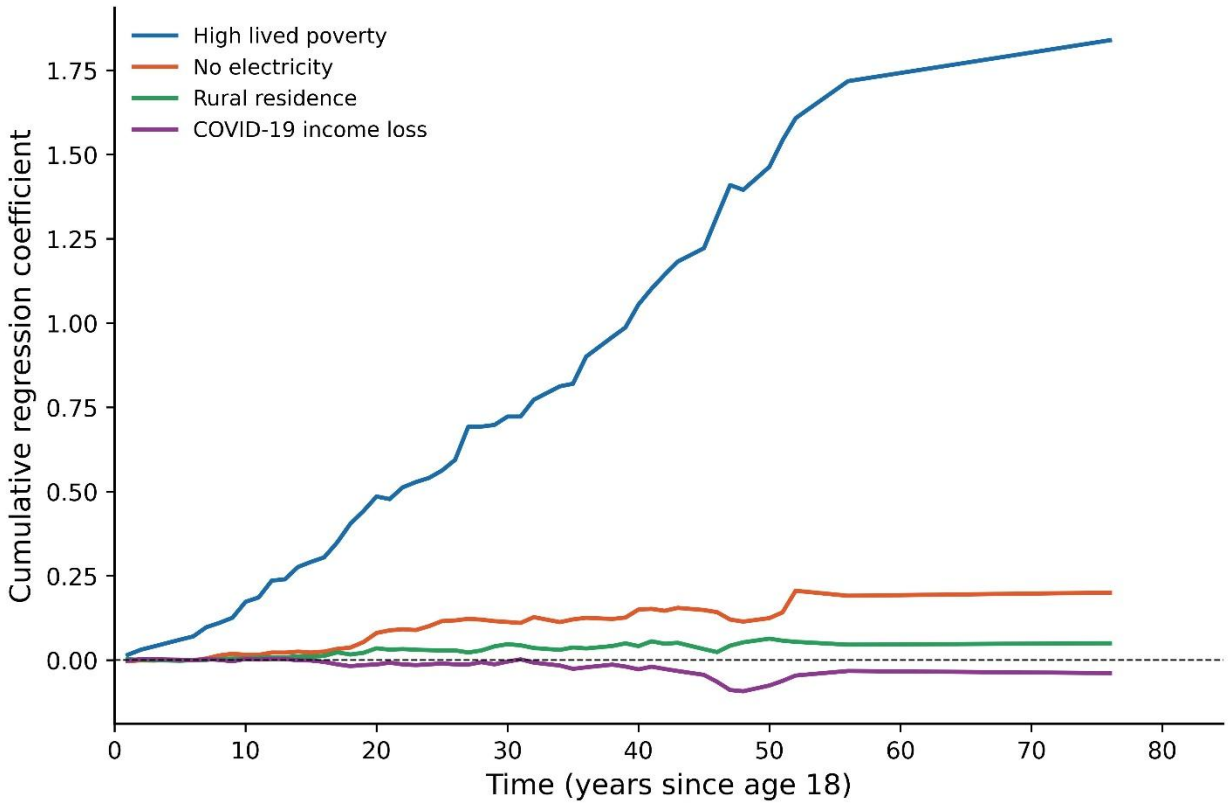


Figure 8: Cumulative regression coefficients from the Aalen additive hazards model for selected predictors, Ghana Afrobarometer Round 9, 2022 (N = 2,268).

The Aalen additive hazards model was estimated with smoothing and coefficient penalisation to reduce instability at sparse event times. Four predictors of primary substantive interest are displayed: high lived poverty, lack of electricity connection, rural residence, and COVID-19 income loss. The vertical axis represents the cumulative additive contribution of each predictor to the baseline hazard over time since age 18; a positive and widening trajectory indicates a sustained positive contribution to the hazard of severe healthcare deprivation. A horizontal reference line at zero is shown for orientation. Trajectories for remaining covariates are omitted from the figure for visual clarity but were estimated in the full model.

Residual Checks (Model Fit Assessment)

Figure 9 displays martingale residuals from the adjusted Cox model. The residual pattern suggests limited non-linearity for most predictors, although age may require centering or spline specification to improve numerical stability.

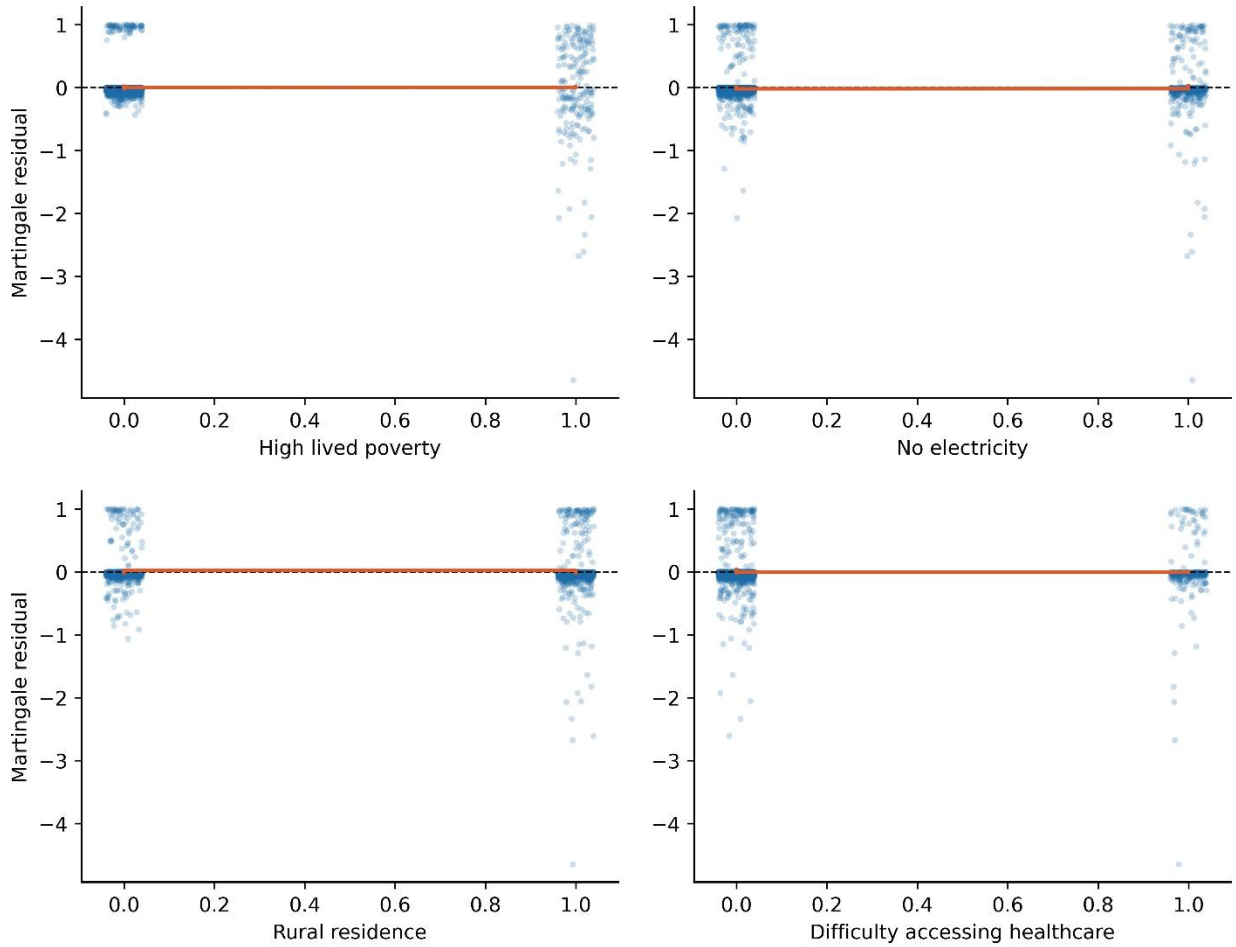


Figure 9. Martingale residuals from the multivariable Cox proportional hazards model plotted against key binary predictors, Ghana Afrobarometer Round 9, 2022 (N = 2,268).

Each panel displays martingale residuals on the vertical axis against the observed value (0 or 1) of the indicated predictor on the horizontal axis. A small random horizontal jitter has been applied to separate overlapping points. The orange line in each panel represents a rolling mean smoother across the covariate axis. The horizontal dashed line at zero is the reference for a well-fitting model. Residuals with values near zero indicate observations well predicted by the model; large positive residuals indicate events that occurred earlier than the model predicted, and large negative residuals indicate censored observations or events that occurred later than predicted. The absence of pronounced curvature in the smoother across covariate values in each panel is consistent with adequate functional form specification for these predictors in the linear component of the Cox model. Panels are shown for high lived poverty (upper left), lack of electricity connection (upper right), rural residence (lower left), and difficulty accessing healthcare (lower right).

Stratified and Sensitivity Analyses

Gender-Stratified Analysis

A gender-stratified Cox regression, allowing separate baseline hazard functions for men and women while constraining covariate effects to be equal across strata, yielded estimates broadly consistent with the primary model (Table 5). High lived poverty remained the strongest correlate of reported severe deprivation (HR = 7.71, 95% CI: 5.72–10.38, p < 0.001), consistent with the primary model estimate after penalisation. Lack of electricity connection (HR = 1.55, 95% CI: 1.20–2.01, p = 0.001), difficulty accessing healthcare (HR = 1.43, 95% CI: 1.07–1.93, p = 0.017), and poor water source (HR = 1.45, 95% CI: 1.11–1.90, p = 0.007) each retained statistically significant positive associations after stratification. Rural residence was not independently associated with the outcome after full adjustment in the gender-stratified model (HR = 1.17, 95% CI: 0.92–1.50, p = 0.197). Female sex showed no independent association (HR = 1.00, 95% CI: 0.69–1.45, p = 1.000), consistent with the primary model. Model discrimination was good (Harrell C = 0.836).

Table 5: Gender-Stratified Cox Proportional Hazards Model (N = 2,268; events = 191)

Variable	***HR***	***95% CI***	***p-value***
Geographic factors			
Rural residence	1.17	0.92–1.50	0.197
Socioeconomic status			
High lived poverty	7.71	5.72–10.38	<0.001
Health system access			
Difficulty accessing healthcare	1.43	1.07–1.93	0.017
Paid bribe for healthcare	1.16	0.74–1.83	0.513
Infrastructure			
No electricity connection	1.55	1.20–2.01	0.001
Poor water source	1.45	1.11–1.90	0.007
Trust and governance			
Low trust in health council	0.90	0.69–1.18	0.436
High corruption perception	1.08	0.85–1.37	0.523
COVID-19 impact			
COVID-19 income loss	0.91	0.70–1.19	0.486
No COVID-19 vaccination	1.06	0.84–1.34	0.636
Demographic factors			

Female sex	1.00	0.69–1.45	1.000
Primary education	1.10	0.85–1.43	0.475
Secondary education	1.02	0.78–1.33	0.913
Post-secondary education	1.03	0.74–1.44	0.862

Baseline hazard functions are estimated separately for men and women. A ridge penaliser (penalizer = 0.05) was applied to stabilise the high lived poverty estimate given the strong imbalance in event rates between poverty strata. Harrell C = 0.836. Reference categories as per primary model.

Regional-Stratified Analysis

Stratification by administrative region, to account for unmeasured regional heterogeneity in baseline healthcare infrastructure and service availability, yielded estimates consistent in direction and approximate magnitude with the primary model for all covariates (Table 6). High lived poverty retained a strong positive association (HR = 7.06, 95% CI: 5.13–9.72, $p < 0.001$). Lack of electricity connection (HR = 1.40, 95% CI: 1.07–1.84, $p = 0.015$), difficulty accessing healthcare (HR = 1.47, 95% CI: 1.08–2.00, $p = 0.014$), and poor water source (HR = 1.44, 95% CI: 1.10–1.89, $p = 0.008$) showed consistent independent associations. Rural residence was not independently associated with the outcome after full adjustment within regions (HR = 1.20, 95% CI: 0.93–1.53, $p = 0.157$), suggesting that the modest rural association observed in unadjusted analysis is at least partly attributable to between-region differences in infrastructure rather than a within-region geographic effect. Model discrimination was good (Harrell C = 0.832).

Table 6: Region-Stratified Cox Proportional Hazards Model (N = 2,268; events = 191)

Variable	***HR***	***95% CI***	***p-value***
Geographic factors			
Rural residence	1.20	0.93–1.53	0.157
Socioeconomic status			
High lived poverty	7.06	5.13–9.72	<0.001
Health system access			
Difficulty accessing healthcare	1.47	1.08–2.00	0.014
Paid bribe for healthcare	1.27	0.79–2.03	0.325
Infrastructure			
No electricity connection	1.40	1.07–1.84	0.015

Poor water source	1.44	1.10–1.89	0.008
Trust and governance			
Low trust in health council	0.94	0.72–1.24	0.676
High corruption perception	1.10	0.86–1.41	0.461
COVID-19 impact			
COVID-19 income loss	0.88	0.67–1.16	0.363
No COVID-19 vaccination	1.09	0.86–1.39	0.468
Demographic factors			
Female sex	1.04	0.78–1.39	0.802
Primary education	1.23	0.93–1.61	0.142
Secondary education	1.10	0.84–1.45	0.498
Post-secondary education	1.00	0.71–1.41	0.983

Baseline hazard functions are estimated separately for each administrative region. A ridge penaliser (penalizer = 0.05) was applied consistent with the gender-stratified model. Harrell C = 0.832. Reference categories as per primary model.

Time-Varying Effects Analysis

An extended Cox model including a rural residence by log-time interaction term was fitted to assess whether the association between geographic location and the hazard of reported severe deprivation changes across the adult lifespan (Table 7). The interaction term was statistically significant (HR = 0.875, 95% CI: 0.80–0.96, p = 0.005), indicating a modest attenuation of the rural association at longer follow-up durations. The main effect of rural residence in this parameterisation represents the estimated association at t = 1 (log-time = 0) and should not be interpreted independently of the interaction term (HR = 1.53, 95% CI: 1.13–2.07, p = 0.006). Taken together, these estimates suggest that any rural disadvantage in reported severe deprivation is more pronounced in early adulthood and diminishes gradually with age, though the magnitude of attenuation is modest and both the main effect and interaction term carry imprecision. This finding warrants consideration in the interpretation of the primary model rural estimate and may reflect survivor selection, changes in rural-urban migration patterns with age, or genuine convergence in access experiences across the lifespan. No causal interpretation is warranted from these cross-sectional data. Model discrimination was Harrell C = 0.848.

Table 7: Time-Varying Effects Analysis for Rural Residence (N = 2,268; events = 191)

Component	***HR***	***95% CI***	***p-value***

Rural residence (main effect at ln(t) = 0)	***1.53***	***1.13–2.07***	***0.006***
Rural × ln(t) interaction	***0.875***	***0.80–0.96***	***0.005***

The main effect represents the estimated hazard ratio for rural residence at t = 1 year since age 18 and should be interpreted jointly with the interaction term. A ridge penaliser (penalizer = 0.05) was applied consistently with other models. Harrell C = 0.848.

Discussion

This study examined socioeconomic, infrastructural, and health system correlates of self-reported severe healthcare deprivation among Ghanaian adults using a retrospective survival analysis framework applied to cross-sectional Afrobarometer data. The findings suggest systematic variation in the age distribution of reported deprivation across poverty, infrastructure, and geographic dimensions, consistent with patterns documented in prior research on health equity in Ghana and sub-Saharan Africa more broadly. All associations reported here are observational and cross-sectional in nature; causal interpretation is not warranted.

Key Findings

High lived poverty was the strongest correlate of reported severe healthcare deprivation in the adjusted model (HR = 12.16, 95% CI: 8.19–18.06). The concentration of events within the high-poverty stratum, 58.7% of high-poverty respondents experienced the outcome compared with 3.5% of low-poverty respondents, is consistent with the inverse care law described by Hart (1971), wherein populations with the greatest need tend to have the least access to adequate care. This pattern is also consistent with prior evidence of wealth-based disparities in National Health Insurance Scheme enrolment and utilisation in Ghana (Dalinjong et al., 2017). The magnitude of the poverty association should nonetheless be interpreted cautiously given the small number of events relative to the degree of imbalance between strata, and the cross-sectional design precludes any conclusion about the direction of this relationship over time.

The observed association between lack of electricity connection and reported deprivation (HR = 1.66, 95% CI: 1.19–2.32) is consistent with prior evidence that electricity constraints limit health facility capacity in sub-Saharan Africa (Adair-Rohani et al., 2013). Electricity availability supports night-time care, medical equipment operation, and cold chain maintenance for vaccines and medicines. The pathway through which this association operates in this sample cannot be established from cross-sectional data, and both direct facility-level and indirect household-level mechanisms remain plausible.

Difficulty accessing healthcare services showed an independent positive association with reported deprivation after full adjustment (HR = 1.60, 95% CI: 1.12–2.29), consistent with prior

evidence that perceived access barriers are associated with unmet healthcare need in low- and middle-income country settings. Rural residence was positively associated with the outcome in unadjusted analysis and in stratified models, though the association was attenuated and no longer statistically significant after full covariate adjustment in the primary model. The larger rural estimate in the gender-stratified model (HR = 1.57) compared with the primary model (HR = 1.22) may reflect confounding redistribution following stratification; whether gender modifies the association between rural residence and healthcare deprivation cannot be determined without a formal interaction analysis.

Low trust in the local government council was not associated with the outcome in either unadjusted or adjusted analyses in the corrected dataset (unadjusted log-rank p = 0.875; adjusted HR = 0.80, 95% CI: 0.57–1.13, p = 0.207). The borderline association reported in an earlier version of this analysis reflected a misspecified event definition and should not be carried forward. Any future investigation of institutional trust as a correlate of healthcare access should use a purpose-designed measure of health system trust rather than the general local government council trust item available in the Afrobarometer instrument.

Comparison with Existing Literature

The dominant role of poverty in the adjusted model is broadly consistent with prior cross-sectional and survey-based evidence from Ghana (Dalinjong et al., 2017; Wongnaah et al., 2025). The rural association, though attenuated after full adjustment, is directionally consistent with documented rural-urban differences in unmet healthcare need (Otieno et al., 2022). The minimal independent associations observed for educational attainment across all model specifications may reflect the specific outcome examined here, severe deprivation in the past year, which may be more proximate to economic and infrastructure constraints than to health literacy or care-seeking behaviour. This interpretation is speculative and the present data do not allow it to be tested directly.

The application of a retrospective survival framework to cross-sectional data offers a complementary perspective on the age patterning of reported deprivation that conventional logistic or linear regression approaches do not provide. However, as discussed in the Limitations section, the cross-sectional design and the nature of the Afrobarometer outcome item constrain what can be inferred about timing, accumulation, or life-course trajectories of healthcare deprivation from these data.

Policy Observations

The findings are consistent with a body of evidence suggesting that healthcare access in Ghana is shaped by factors that extend beyond the health system itself. Poverty and basic infrastructure deficits showed the strongest independent associations with reported deprivation in this sample, and both are amenable to policy intervention, though the mechanisms and appropriate policy responses are complex and cannot be derived from an observational cross-sectional study alone.

Programmes targeting economic deprivation, such as the Ghana Livelihood Empowerment Against Poverty initiative, may have indirect health access benefits, though the evidence base for

such spillover effects remains limited and mixed (Handa et al., 2013). The association between electricity access and reported deprivation is consistent with arguments for prioritising energy infrastructure in health facility development, including solar-powered facility programmes piloted in northern Ghana. Geographic disparities in the availability of community-level health services, as addressed through the Community-based Health Planning and Services initiative, may also be relevant, though the present study cannot identify the specific service-level factors driving the observed associations.

These observations are offered as hypothesis-generating rather than prescriptive. Establishing the causal pathways underlying these associations and identifying effective policy responses requires prospective, longitudinal, and where feasible experimental evidence beyond the scope of this study.

Limitations

Several limitations should be considered when interpreting these findings. The Afrobarometer survey item used to define the outcome asks about experience in the past year and does not ask respondents to identify their first-ever lifetime episode of healthcare deprivation. The survival framework therefore imposes a first-event interpretation on a recent prevalence measure, and all time-based estimates reflect the cross-sectional age distribution of reported deprivation rather than confirmed incidence timing.

The cross-sectional design introduces survivor bias: individuals who experienced the most severe and sustained deprivation and died or emigrated before the survey are absent from the sample. This form of left truncation is most consequential at older ages and likely results in underestimation of deprivation rates in older age groups. A pre-specified sensitivity analysis restricted to respondents under 50 years yielded associations consistent in direction and approximate magnitude with the full-sample estimates, providing limited reassurance that survivor selection did not materially distort the primary findings, though this analysis does not eliminate the concern.

All predictors are measured at the time of interview and treated as fixed covariates. Time-varying exposure to poverty, electricity access, or geographic location over the respondent's adult life cannot be captured in this design, and the associations reported here reflect current status rather than cumulative exposure history.

Self-reported outcome measurement introduces the possibility of recall bias and differential reporting across socioeconomic groups. Respondents with lower health literacy may not recognise healthcare deprivation in the terms used by the survey item, and social desirability effects may lead to underreporting in some contexts. Unmeasured confounding by health status, transport access, social support, and specific insurance enrolment details remains a limitation that cannot be addressed with the available data.

Finally, the small number of events relative to the number of covariates (191 events across 14 predictors) limits the precision of several estimates, particularly for less prevalent exposures, and increases the risk that observed associations are unstable. These findings should be regarded as

preliminary and replicated in larger samples or prospective designs before informing policy decisions.

Conclusion

Severe healthcare deprivation among Ghanaian adults is not uniformly distributed across the population but shows strong and consistent patterning along socioeconomic and infrastructural lines. Across all model specifications, high lived poverty was the dominant correlate of reported deprivation, with high-poverty respondents experiencing the outcome at a rate more than twelve times that of low-poverty respondents after full covariate adjustment. This finding persisted after gender stratification, regional stratification, and penalised estimation, lending consistency to the observed association. Lack of reliable electricity and self-reported difficulty accessing healthcare services each showed independent positive associations of moderate magnitude, remaining statistically significant across primary and stratified models. These three factors — economic deprivation, infrastructure deficit, and perceived access barriers — represent the clearest and most replicable signal in this dataset.

Several variables that feature prominently in the health equity literature showed little independent association in the adjusted analyses. Rural residence, while positively associated with deprivation in unadjusted comparisons, was attenuated after adjustment for poverty and infrastructure, suggesting that the rural disadvantage observed in this sample operates substantially through those pathways rather than through geography alone. Educational attainment, gender, institutional trust, COVID-19 related exposures, and corruption perception showed no statistically significant independent associations after full adjustment, and their wide confidence intervals preclude firm conclusions about the absence of association in the underlying population.

The time-varying analysis indicated a modest attenuation of the rural association at older ages, and the survival framework revealed that reported severe deprivation is concentrated in the working-age adult years rather than being uniformly distributed across the lifespan, which has implications for the targeting of interventions toward younger and economically active age groups.

Taken together, these findings suggest that efforts to reduce severe healthcare deprivation in Ghana may need to address material living conditions and physical access to services alongside conventional health system strengthening. The strong and consistent poverty association is compatible with arguments for integrating health access objectives into broader economic and social protection programmes, including pro-poor health financing mechanisms and infrastructure investment in underserved communities. The electricity association points specifically to health facility functionality as a proximate constraint, consistent with evidence from other sub-Saharan African settings that energy access limits the range and quality of services that facilities can deliver.

These conclusions are appropriately bounded by the observational and cross-sectional nature of the study. The associations reported here are estimated from a single cross-sectional survey, and neither the direction of causality nor the specific mechanisms linking poverty and infrastructure deficits to healthcare deprivation can be established from these data. Prospective and longitudinal designs, ideally tracking individuals over time with objective measures of both healthcare utilisation and material living conditions, are needed to strengthen causal inference and to identify the points in the deprivation pathway most amenable to intervention. Notwithstanding these limitations, this study provides a methodologically transparent and empirically grounded account of the socioeconomic and infrastructural patterning of severe healthcare deprivation in Ghana, and contributes to the evidence base informing health equity research and policy in West Africa.

Declarations

Ethics approval and consent to participate

This study is a secondary analysis of anonymised, publicly available survey data from Round 9 of the Afrobarometer survey. The Afrobarometer surveys are conducted in accordance with rigorous ethical standards, including informed consent from all respondents at the time of data collection. Ethical approval for the original Afrobarometer survey was obtained from institutional review boards in the participating countries in accordance with national regulations. For this secondary analysis, no further ethical approval was required as the data are publicly available and fully anonymised. All methods were performed in accordance with relevant guidelines and regulations of the declaration of Helsinki.

Consent for publication

Not applicable. This manuscript contains no individual person's data in any form.

Availability of data and materials

The data that support the findings of this study are publicly available from the Afrobarometer data repository. Afrobarometer Round 9 survey data for Ghana can be accessed at https://www.afrobarometer.org/ after free registration. The analytical code used for this study is available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

RBA conceptualised the study, performed the statistical analysis, and drafted the manuscript. CP contributed to the study design, data interpretation, and critical revision of the manuscript. JKG contributed to the acquisition of data, interpretation of results, and revision of the manuscript. All authors read and approved the final manuscript.

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