Heterogeneous Effects of Demographic Factors on Healthcare Utilisation in Ghana

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Abstract

The purpose of this paper is to examine the heterogeneous effects of demographic factors on healthcare utilisation. The two-stage residual inclusion (2SRI) strategy was utilised in the study to address the endogeneity problem. The study discovered significant differences in the utilisation of healthcare services based on age distribution and gender after decomposing the data. Based on age distribution disaggregated data, the study discovered considerable differences in the use of healthcare services. According to the age distribution subsample analysis, gender, education, and obesity were the variables that determined healthcare utilisation for the working class, whereas locality (rural) determined utilisation for the elderly. Physical inactivity was the only variable that influenced the working class and the elderly use of healthcare. For children, those from the working class, and the elderly, healthcare use was commonly determined by NHIS membership, self-assessed health, chronic illness and type of illness. Furthermore, the study found significant variations in healthcare utilisation when the analysis was based on gender. For the children subsample, self-assessed health and chronic illness determined females' healthcare utilisation. Working-class males' healthcare use was influenced by education, but females' healthcare use was affected by NHIS participation, obesity and physical inactivity. Finally, chronic sickness and diarrhoea affected how elderly males used healthcare, whereas NHIS membership, physical inactivity, and location (rural) affected elderly females' healthcare utilisation. The study suggests that age and gender information be taken into account when developing, planning, and implementing healthcare policy to increase the use of healthcare services.

Keywords: *demographic factors, healthcare utilisation, two-stage residual inclusion*

Introduction

The population's demographics, including projected or expected changes, affect the "universal" requirement for health and well-being (Szabo et al., 2020). Demography studies population dynamics, including size, distribution, age, and gender. The population's size and age distribution significantly impact the demand for health services. For instance, the demand for hospitalisation services is associated with age, with elderly patients having a higher likelihood of admission and extended hospital stays. Numerous diseases are common among older persons, and healing during old age is typically slower. Many therapies are palliative rather than curative, and the chances of developing a new disease or condition rise with age.

While older persons generally require more medical care than younger people, they also have significant barriers to receiving appropriate, affordable, and high-quality treatment.

Demographic changes impact the level and composition of health care needs of the people. Demographic change can influence the economy's underlying growth rate, structural productivity growth, living standards, savings rates, consumption and investment (Mester, 2018). It can also affect housing market trends, the demand for financial assets, the long-run unemployment rate, and the equilibrium interest rate. Additionally, it is projected that variations in demographic patterns among nations may affect current account balances and exchange rates (Mester, 2018).

The empirical literature on healthcare utilisation is quite extensive (Han-Kim & Lee, 2016; Li et al., 2016; Lotfi et al., 2017; Masiye & Kaonga, 2016; Rimes-Dias et al., 2022). A substantial number of the previous studies aggregate the data in their analyses. However, few studies only look at the utilisation of healthcare by the elderly (Gong et al., 2016; Grustam et al., 2020; Lartey et al., 2020). Studies of this kind help researchers and policymakers to understand the determinants of healthcare utilisation among such vulnerable groups. To the best of the authors' knowledge, no study has disaggregated household data to analyse the determinants of healthcare utilisation based on demographic factors, particularly age and gender. Hence, the objective of this study is to examine the heterogeneous effects of demographic factors on healthcare utilisation. This study is the first to disaggregate household data in Ghana to provide comprehensive estimates of healthcare utilisation for different age distributions and gender. Our comprehension of the heterogeneous effects of the demographics on healthcare utilisation will offer vital insights into the design, planning and management of healthcare policies because information on the influence of age and gender on the utilisation of healthcare services is essential for developing better and appropriate services.

Literature review

Detailed scrutiny of the previous studies shows that each of these studies varies in its operationalisation of healthcare utilisation, methods and variables used. Various authors used different techniques to operationalise healthcare utilisation. Measurement of healthcare utilisation includes outpatient visits or inpatient care (Ekman, 2007; Liu & Zhao, 2014; Saeed et al., 2015), preventive care (O'Connor, 2015), and number of doctor visits (Ekman, 2007; Hullegie & Klein, 2010). Other authors used the number of nights spent at a hospital (Saeed et al., 2015; Sengupta & Rooj, 2019) and the number of antenatal care visits (Sanogo & Yaya, 2020).

Another part of the empirical evidence reveals studies that assumed the health insurance variable to be exogenous. These studies employ either only binary logistic regressions or binary logistic regressions (O'Connor, 2015) and Poisson regression with its extension in the form of negative binomial model (Ekman, 2007; Geitona et al., 2007). These studies, which failed to address the endogeneity problem, leading to selection bias, are likely to overestimate the impact of health insurance on healthcare utilisation. In contrast, some authors recognised the problem of endogeneity when modelling the effect of health insurance on healthcare utilisation. Different authors use various approaches to correct for possible endogeneity of health insurance. These approaches include bivariate probit estimation technique (Waters, 1999), instrumental variable method (Gajate-Garrido & Ahiadeke, 2013; Liu & Zhao, 2014), propensity score matching (Bonfrer et al., 2016; Gouda et al., 2016), difference-in-differences approach (Idris et al., 2017) and regression discontinuity analysis (Hullegie & Klein, 2010).

Considering the determinants of healthcare utilisation, aside from health insurance, Geitona et al. (2007) found age, income, gender (female), and region to have a positive influence on primary health care services. In contrast, self-rated health status had a negative relationship with the frequency of visits for primary health care. On the contrary, Ekman (2007) does not find any significant association of income, insurance, sex and education on the probability of visiting a health service provider. One notable finding of this study was that older people increasingly seek less care. The study further revealed that self-reported worse health persons and chronic illness individuals increase healthcare utilisation significantly. In a study conducted in Northern Cyprus, Abuduxike et al. (2020) evaluated the factors influencing healthcare utilisation and the health-seeking behaviours of individuals using public and private healthcare facilities. Their findings revealed that people who were current smokers, had chronic conditions, had poor perceptions towards their health, and had spent less on their health in the previous three months were about twice as likely to have regular check-ups. Higher educational levels predicted health-seeking behaviours positively. But individuals with self-care problems and modest incomes were found to be negatively related to healthcare utilisation.

Recently, Hone et al. (2022) used Andersen's behavioural model of healthcare utilisation and multivariate logistic regression to explore the relationship between predisposing, enabling, and need factors with outpatient and inpatient health services. They discovered that men used outpatient services less frequently. Low social support, poor general health, and time away from work due to illness were strongly correlated with outpatient utilisation. Higher educational level, poor overall health, and absence from work due to sickness were linked to greater use of inpatient care. In China, Chen and Liu (2022) examined the determinants of primary care utilisation among older people with multiple illnesses. Regarding outpatient utilisation, older women, those who were married, those who lived in rural areas, and those with poor self-rated health had a significantly higher probability of using outpatient care. However, the likelihood of seeking outpatient treatment was much lower for those with a middle school education and better household finances. In another recent study conducted in Brazil, Rimes-Dias et al. (2022) analysed the relationship between obesity and healthcare utilisation, considering services for people with diabetes and or hypertension. The researchers discovered that respondents with obesity (both male and female) used all health care services around twice as often as underweight or normal-weight people. In comparison to men who were underweight or normal weight, obese men with hypertension were more likely to use hospitalisation services. Obese women with diabetes received more expert referrals and consultations than underweight or normal-weight women.

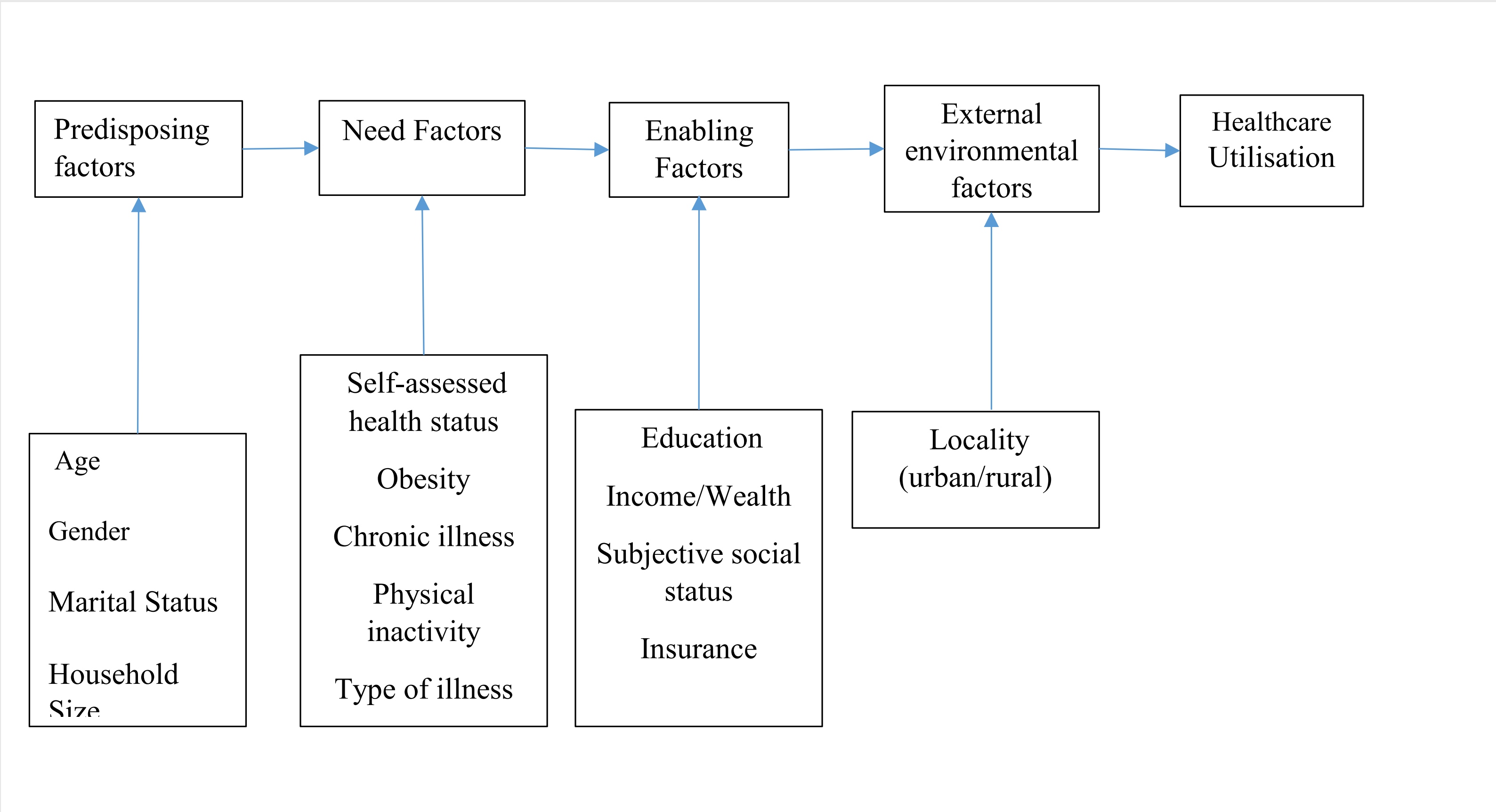
The empirical literature on healthcare utilisation is quite extensive, with a substantial number of these studies aggregating data in their analyses. Few studies, meanwhile, focus solely on how the elderly use healthcare. This paper contributes to the literature by disaggregating household data to analyse the determinants of healthcare utilisation based on demographic factors, particularly age and gender. As a result, this study provides a comprehensive estimate of healthcare utilisation for various age distributions and gender.

Methodology

Conceptual framework

The current study adopts a modified version of the Andersen (1995) behavioural model framework for healthcare utilisation to identify factors that potentially promote or hinder individuals' visits to the health facility. The model predicts that a series of factors categorised under predisposing, enabling and need factors determine healthcare utilisation. Sociodemographic characteristics such as age, gender and household size are all predisposing factors. Individuals' use of services is facilitated or hampered by enabling factors. Education, subjective social status, insurance, and distance to a health institution are all enabling variables.

Figure 1: Conceptual framework for healthcare utilisation



Lastly, need factors are overall health conditions which motivate individuals' service use. These factors include self-assessment health status, chronic illness and physical inactivity. The current study adds an external factor measured by locality (urban or rural). In Ghana, urban and rural areas differ in the areas of social and economic development. Thus, the inclusion of this variable would help examine inequity in healthcare utilisation. Generally, the utilisation of healthcare services is influenced by individual and household specific variables, including age, gender, education, social status, locality (urban or rural), among others. Figure 1 gives a snapshot of the conceptual framework for health service utilisation as a modification of Andersen's behavioural model.

Data

This empirical analysis is based on data from the Ghana Socioeconomic Panel Survey (GSPS). The Economic Growth Centre at Yale University and the Institute of Statistical, Social, and Economic Research (ISSER) at the University of Ghana collaborated in conducting this survey. The study used a total of 31,807 individuals from the first three waves. The dataset includes data on households' demographics, assets, housing characteristics, consumption modules, household health (including data on insurance status, anthropometry, activities of daily living, miscellaneous health, health in the past two weeks, and health in the past 12 months before the survey), and the like. The survey employed a two-stage stratified sample methodology for data gathering. Enumeration areas (EAs) were chosen in the first step, and 15 households were randomly selected from each EA in the second stage across Ghana's former ten administrative regions.

Econometrics approach

To investigate the determinants of healthcare utilisation, a logit model is used. It is appropriate to apply this model since the dependent variable, a visit to a health facility, is a binary outcome. The logistic regression model that expresses the probability of using healthcare services as a function of a set of independent variables appears in this form:

$$Pr(Y_i) = F(\alpha_i + X_i\beta + \varepsilon_i)\ ; \quad i = 1, 2, \ldots, n; \qquad (1)$$

where $Pr(Y_i)$ represents the likelihood of selecting one of the response outcomes (visit to a healthcare facility). α_i, intercept; β, vector of parameter estimates; X_i, vector of independent variables; ε_i, error term; F is the cumulative logistic distribution of the form

$$F(z) = \frac{exp\ (z)}{1 + exp\ (z)}$$

Health insurance, chronic illness, physical inactivity, type of illness, obesity, age, gender, education, place of residence, wealth, and self-assessed health are among the many variables that influence healthcare utilisation. In Ghana, since the government introduced the National Health Insurance Scheme (NHIS) in 2003, health insurance continues to be a crucial determinant of healthcare utilisation. Therefore, it is essential to consider health insurance while estimating healthcare utilisation. However, there is a methodological challenge when one models the effects of health insurance on healthcare utilisation. When modelling the influence of health insurance on healthcare utilisation, several academics have identified the endogeneity problem and have corrected it (Gouda et al., 2016; Idris et al., 2017; Liu & Zhao, 2014). Our identification strategy encompasses estimating a two-stage residual inclusion [2SRI] to account for the endogeneity of the health insurance variable (Terza et al., 2008). To break the correlation between the endogenous explanatory variable and the unobserved heterogeneities affecting the outcome variable, the 2SRI inserts an additional regressor as a control function strategy (Wooldridge, 2010).

The study adhered to Terza's (2017) guidelines for modelling the 2SRI. The first stage of the 2SRI estimation consists of predicting the residual of the endogenous regressor. The likelihood of enrolling in health insurance is estimated using a logit model by regressing the health insurance variable on the instrument(s) and other exogenous variables as shown below:

$$HI\ \text{enrolment}_i = \alpha_0 + \alpha_1 IV_i + \alpha_2 X_i + \mu_i \qquad (2)$$

where HI enrolment_i takes the value of one (1) if an individual decides to enrol in NHIS and zero (0) otherwise, IV_i is a vector of the instrumental variables, X_i represents a set of exogenous independent variables theorised to affect *HI* enrolment and ε_i is the error term. The elements in *IV* should satisfy the following conditions: firstly, they cannot be correlated with μ_i; second, they should sufficiently correlate with the endogenous variable (i.e., HI enrolment); and lastly, they can neither have a direct impact on the outcome variable (i.e., visits to a healthcare facility) nor correlate with the error term in (1). Moreover, there should be at least as many elements in IV as there are endogenous regressors in (1).

The residuals from the first stage regression are used as a regressor in the second stage of the 2SRI model, which entails fitting a logit model of the outcome (a visit to a healthcare facility) on all other explanatory variables. The second stage model would be expressed as follows:

$$Pr(Y_i) = F(\alpha_i + X_i\beta + \delta_i Res + \varepsilon_i^{2SRI})\ ; \quad i = 1, 2, \ldots, n; \qquad (3)$$

Where Res denotes the estimated residuals from the first stage regression estimation and ε_i^{2SRI} is the error term from the second stage estimation. However, the standard errors gotten at this point are incorrect but bootstrapping can be used to obtain the correct standard errors. In this study, formal sector Work (T) served as an instrumental variable. Ghanaian law mandates that all formal-sector employees contribute to the Social Security and National Insurance Trust (SSNIT). As a result, nearly all formal-sector workers are SSNIT contributors. Formal-sector workers are required by the statute that created Ghana's NHIS to donate 2.5% of their SSNIT contribution to the NHIS. Additionally, SSNIT contributors are required by law to enrol in the NHIS without paying a premium. We concluded that our instrument, formal-sector work, would be a reliable indicator of NHIS enrolment. However, the formal-sector work variable may not be a reliable indicator of whether or not a person will attend a healthcare facility. Although institutional mechanisms in the formal sector may require employees to use health care facilities, we found this requirement is not universally enforced in the Ghanaian context, at least not for a sizable portion of the formal sector workforce. As a result, we anticipate that our instrument variable will meet the external validity requirement. To verify this assertion, we also ran a pseudo-regression of the outcome variable on the instrument variable, adjusting for potential confounding variables (see Table A2). Table 1 encapsulates the descriptive statistics and measurement of the variables used in the analysis.

Table 1: Variables, measurement and descriptive statistics

Variable	Measurement	Mean	SD
Dependent variable			
Visit to health facility	Dummy: 1 = Visit to health facility; 0 = otherwise	0.084	0.278
Independent variables			
NHIS enrolment	Dummy: 1 = currently insured; 0 = otherwise	0.503	0.500
Gender	Dummy: 1 = male; 0 = otherwise	0.473	0.500
Age	Continuous: positive whole numbers in years	34.895	19.953
Education	Ordinal: measured on a five-point scale ranging from 0 for no formal education to 4 as the highest educational level attained	0.463	0.812
Locality (rural)	Dummy: 1 = resides in rural area; 0 = otherwise	0.651	0.477
Obesity	Dummy: 1 = if BMI ≥30; 0 = otherwise	0.100	0.299
Fever	Dummy: 1 = if suffered Fever; 0 = otherwise	0.036	0.187
Cold or cough	Dummy: 1 = if suffered Cold or Cough; 0 = otherwise	0.009	0.094
Diarrhoea	Dummy: 1 = if suffered diarrhoea; 0 = otherwise	0.003	0.059
Chronic illness	Dummy: 1 = if exposed to chronic illness (sores, irritations and/or numbness); 0 = otherwise	0.282	0.450
Self-assessed health	Ordinal: unhealthy =1, somewhat unhealthy =2, somewhat healthy =3 and Very healthy =4	3.681	0.628
Physical inactivity	Dummy: 1 = difficulty in participating in physical activities/roles; 0 = otherwise	0.135	0.341
Wealth index	Continuous positive and negative numbers generated from housing and assets characteristics using Multiple Correspondence Analysis	-0.217	1.234

Note: Body Mass Index is weight in kg divided by height in centimetres squared multiply by 10,000; SD is the standard deviation

Results and discussion

Heterogeneous determinants of healthcare utilisation by age subpopulations

The regression estimates of the heterogeneous determinants of healthcare use by age subgroups are shown in Table 2. The study reports only marginal effects estimates since the first stage estimation gives the direction and not magnitude of the effects. The advantage of the 2SRI is that it offers a straightforward means of determining whether the endogenous explanatory variable is, in fact, endogenous by observing the residuals. The residual coefficient is statistically significant and negative in the pooled and age groups, demonstrating that the NHIS variable is endogenous (see Table 2). The negative coefficient shows that latent characteristics that affect a person's likelihood of being an NHIS member also decrease their propensity to seek care.

The findings show that NHIS, gender, level of education, obesity, self-assessed health, chronic illness, fever, cold or cough and diarrhoea and locality (rural) are significant drivers of healthcare usage for the pooled sample. The findings indicate that NHIS membership positively affects healthcare use across all age groups. These results suggest that NHIS members of all age groups are more likely than those without insurance to attend a hospital when ill. To put it another way, NHIS members are more likely to seek medical attention when sick, regardless of age. For insured individuals of all ages, the marginal effect estimates indicate rising probabilities of healthcare utilisation, with children, working-age adults, and the elderly displaying respective rates of 4%, 5.5%, and 25.6%. These results demonstrate that NHIS members are more likely to visit a health facility as they get older. This finding, in particular for the elderly, may be explained by the NHIS law's exemption of the elderly (those over 70 years old) from paying premiums, leading to increased enrolment for the elderly. This pattern of results is consistent with the body of literature and supports earlier findings that health insurance increases the use of healthcare services (Lartey et al., 2020; Madyaningrum et al., 2018; Van Der Wielen et al., 2018). For example, studies in Ghana found increased health service utilisation among insured older adults (Lartey et al., 2020; Van Der Wielen et al., 2018).

Table 2: Two-stage residual inclusion estimates for healthcare use

Variable	Pooled	Children (< 15 years)	Working-class (ages 15 to 59)	Elderly (=>60 years)
NHIS membership	0.105*** (0.018)	0.040*** (0.016)	0.055*** (0.013)	0.256*** (0.047)
Gender (male)	-0.015*** (0.003)	0.001 (0.004)	-0.020*** (0.004)	0.007 (0.011)
Education	0.007*** (0.002)	0.005 (0.007)	0.005** (0.002)	-0.002 (0.007)
Obesity	0.012*** (0.004)	-0.0001 (0.011)	0.013*** (0.005)	-0.016 (0.014)
Self-assessed health	-0.049*** (0.002)	-0.014*** (0.005)	-0.043*** (0.002)	-0.057*** (0.006)
Chronic illness	0.033*** (0.003)	0.013* (0.008)	0.030*** (0.004)	0.031*** (0.010)
Physical inactivity	0.007 (0.004)	-0.004 (0.004)	0.026*** (0.009)	0.029** (0.012)
Wealth index	0.002 (0.002)	0.003 (0.002)	-0.001 (0.002)	0.007 (0.007)
Fever	0.131*** (0.004)	0.188*** (0.043)	0.245*** (0.018)	0.312*** (0.038)
Cold or cough	0.113*** (0.010)	0.155*** (0.083)	0.226*** (0.034)	0.174*** (0.064)
Diarrhoea	0.135*** (0.015)	0.197*** (0.098)	0.344*** (0.071)	0.197** (0.127)
Locality (rural)	-0.009** (0.004)	-0.006 (0.006)	-0.003 (0.004)	-0.035*** (0.012)
Residuals	-0.031*** (0.008)	-0.011* (0.006)	-0.012** (0.005)	-0.077*** (0.023)
Observations	31,807	5,753	21,679	4,375
Wald χ^2	2,701.70***	154.70***	1,778.98***	504.50***
Log likelihood	-7,695.834	-773.223	-5,201.026	-1,642.022
Pseudo R^2	0.1618	0.0849	0.1506	0.1572
Model classification	91.65%	96.61%	91.86%	84.05%

Notes: ME is marginal effects; Bootstrapped standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

Aside from the pooled sample, gender is a negative predictor of healthcare utilisation for persons within the working age. This result implies that working-age males are less likely to seek medical attention when sick. The marginal effect predicts a two percentage point reduction in the likelihood of working-age males seeking medical attention while ill. A possible explanation for this finding is that the opportunity cost for seeking care earlier may be high for males within the working age because of possible income loss. Hence, when an ailment first appears, persons within the working age group are more likely to put off getting assistance, decreasing their visits to a medical facility. Previous studies have generally found that males use healthcare less frequently because women have greater health demands and awareness than men (Han-Kim & Lee, 2016; Li et al., 2016).

Education and obesity are positive predictors of healthcare utilisation for persons within the working age. These results imply that the more educated and obese persons in the working age group are, the more likely they will visit a health facility when sick. The finding on education is consistent with previous studies (Gong et al., 2016; Grustam et al., 2020; Li et al., 2016; Ye et al., 2019). Ye et al. (2019) argued that people with higher levels of education are more health-conscious resulting in increased healthcare utilisation. This finding contradicts the work of Lotfi et al. (2017). The authors suggested that the more educated individual devotes more attention to health-related concerns and regularly utilises preventative measures, leading to improved health outcomes, thereby reducing the utilisation of healthcare services. Obesity among the working age adults is the main driver of healthcare utilisation in the pooled sample. In Brazil, utilisation of all healthcare services was almost doubled due to obesity in both men and women (Rimes-Dias et al., 2022).

Self-assessed health has a negative effect on healthcare utilisation for all age strata. The results show decreasing probability of healthcare utilisation of 1.4%, 4.5% and 5.7% for children, the working age adults and the elderly, respectively. These results show that the likelihood of using healthcare decreases as people rate their health as very good, irrespective of age category. This result is consistent with earlier research (Grustam et al., 2020; Madyaningrum et al., 2018).

The variable chronic illness positively influences utilisation across all age groups. These results indicate that the likelihood of utilising care increases for persons with chronic ailments, irrespective of age. The results reveal an increasing probability of healthcare usage of 1.3%, 3% and 3.1% for children, working adults and the elderly, respectively. This observation corroborates the findings of Gong et al. (2016), Han-Kim & Lee (2016) and Li et al. (2016).

Physical inactivity positively determines healthcare utilisation for the working class and the elderly. This result implies that persons in the working age group and the elderly who have difficulties participating in physical activities/roles are more likely to utilise healthcare. For both the working class and the elderly, the likelihood of obtaining care rises by 2.6 and 2.9 percentage points, respectively. Some individuals in the working class and the elderly are more likely to have difficulties participating in physical activities and may have health issues relative to children. These health problems are often associated with ageing resulting in increased healthcare utilisation.

The effects of type illness of dummies are statistically significant and positive, indicating that those who have a fever, cold or cough and diarrhoea are more likely to use care when sick relative to sufferers of other illnesses. This finding is intriguing because it demonstrates how people of all ages seek medical attention as soon as these illnesses manifest, preventing delays in receiving care. These results are similar to findings in a study in Ghana by Sekyi and Domanban (2012). Masiye and Kaonga (2016) discovered that fever sufferers in Zambia were more likely to seek formal care than those with diarrhoea and headache.

Locality (rural) negatively determines utilisation for the elderly subsample, and is a key influencer in the pooled sample. The implication of the negative effect of locality on the utilisation of healthcare for the elderly is that the aged residing in rural areas are less likely to visit a health facility when sick. This finding is worrying as it reveals a disproportionate healthcare system that disadvantages the aged who need care during their old age. The uneven distribution of health facilities skewed in favour of urban residents, and distance to healthcare facilities are likely to make the rural elderly resort to healthcare alternatives such as self-medication and traditional medicine. This result confirms the study conducted by Masiye and Kaonga (2016).

Heterogeneous effects of healthcare utilisation by age and gender

Since there are significant gender disparities in the usage of healthcare services, the analyses are done separately for males and females. The regression estimates of the factors influencing healthcare use by age and gender subpopulations are shown in Table 3. The findings show that with the exception of male children, females of all age groups with active NHIS membership are more likely to use healthcare services than males. The marginal effect estimates reveal increasing probabilities of care used for insured females, with children, working-age adults and elderly showing 5.4%, 10.3% and 43.7%, respectively. For working age, education and obesity are positive predictors of healthcare utilisation for males and females, respectively. These findings suggest that among people of working age, males with higher levels of education are more likely to seek medical attention while ill, although obese females are also more likely to do so. These results are fascinating because they reveal which of these genders contributes to the significance of these variables. Disaggregating the data based on gender shows that educated males and obese females account for the influence of the education and obesity variables when the analysis is done on age distribution alone.

Table 3: Heterogeneous effects of healthcare utilisation by age and gender

Variable	Children (< 15 years)		Working-class (15 to 59 years)		Elderly (=>60 years)	
	Males	Females	Males	Females	Males	Females
NHIS membership	0.043**	0.054**	0.014	0.103***	0.102	0.437***
	(0.019)	(0.026)	(0.018)	(0.021)	(0.068)	(0.073)
Education	0.006	0.005	0.009***	0.000	0.004	-0.002
	(0.011)	(0.011)	(0.002)	(0.004)	(0.008)	(0.016)
Obesity	0.007	-0.006	0.013	0.016**	-0.054	-0.005
	(0.018)	(0.017)	(0.008)	(0.007)	(0.035)	(0.021)
Self-assessed health	-0.011	-0.020***	-0.042***	-0.057***	-0.068***	-0.057***
	(0.009)	(0.007)	(0.004)	(0.004)	(0.009)	(0.009)
Chronic illness	0.005	0.020**	0.031***	0.031***	0.044***	0.024
	(0.010)	(0.009)	(0.005)	(0.005)	(0.016)	(0.016)
Physical inactivity	-0.013	0.006	-0.017	0.047***	0.025	0.049***
	(0.008)	(0.007)	(0.014)	(0.010)	(0.020)	(0.018)
Wealth index	0.003	0.006	-0.003	-0.001	-0.017*	0.023**
	(0.004)	(0.004)	(0.002)	(0.003)	(0.010)	(0.010)
Fever	0.074***	0.067***	0.107***	0.148***	0.204***	0.202***
	(0.013)	(0.012)	(0.007)	(0.008)	(0.026)	(0.024)
Cold or cough	0.053**	0.089***	0.098***	0.138***	0.102*	0.155***
	(0.021)	(0.027)	(0.014)	(0.017)	(0.054)	(0.050)
Diarrhoea	0.044**	0.089***	0.124***	0.170***	0.221***	0.079
	(0.020)	(0.022)	(0.021)	(0.031)	(0.079)	(0.095)
Locality (rural)	0.000	-0.013	-0.001	-0.006	-0.028	-0.041**
	(0.008)	(0.010)	(0.005)	(0.007)	(0.018)	(0.017)
Residuals	-0.014*	-0.016	0.002	-0.028***	-0.001	-0.134***
	(0.008)	(0.011)	(0.008)	(0.009)	(0.031)	(0.032)
Observations	3,041	2,710	9,995	11,684	2,007	2,368
Wald χ^2	72.20***	107.02***	661.31***	968.04***	198.90***	249.92***
Log likelihood	-415.905	-350.945	-1,843.898	-3,338.081	-676.900	-954.000
Pseudo R^2	0.0616	0.1262	0.1543	0.1363	0.1745	0.150
Model classification	96.68%	96.57%	94.24%	89.68%	86.50%	82.18%

Notes: ME is marginal effects; Bootstrapped standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0$.

Regarding self-assessed health, the findings indicate that, except for male children, people are less likely to seek medical attention if they rate their health as very good, regardless of gender for the various age categories. Female children, both genders within working adults and aged males with chronic ailments, have an increased probability of utilising healthcare services. According to gender-specific data analysis, working-class and elderly females contribute to the influence of physical inactivity on healthcare utilisation. These results imply that working adults and the elderly who have difficulties participating in physical activities/roles are more likely to use healthcare. The marginal effects suggest that the likelihood of female working adults and the elderly obtaining care when ill increases by 4.7 and 4.9 percentage points, respectively.

Interesting findings are obtained for the wealth index variable. Wealthy elderly males are less likely to utilise healthcare when ill, whereas the reverse finding is obtained for females. Both effects cancel each other out, making the combined effect insignificant when the analysis is done on age. Concerning the type of illness, the findings indicate that except for the elderly female who suffered from diarrhoea, individuals are more likely to seek medical attention when ill, regardless of gender for the various age categories. Last but not least, the use of healthcare is significantly influenced by elderly rural women. The findings show that older females who live in rural locations are less likely to seek medical attention when ill.

Conclusion

The study examined the heterogeneous effects of demographic factors on healthcare utilisation. The study employed the two-stage residual inclusion (2SRI) method to address the methodological challenge of endogeneity when modelling the effects of health insurance on healthcare utilisation. The results revealed that predictors of healthcare utilisation for the pooled sample were NHIS membership, gender, education, obesity, self-assessed health, chronic illness, type of illness suffered and locality (rural). After disaggregating the data, the study found significant disparities in the usage of healthcare services based on age distribution and gender. Based on the age distribution subsample analysis, gender, education, and obesity were the factors that determined healthcare use for the working class, while locality (rural) determined utilisation for the elderly. The only factor that affected the working class and the elderly's use of healthcare was physical inactivity. However, NHIS membership, self-assessed health, chronic illness and type of illness suffered were common determinants of healthcare utilisation for children, the working class and the elderly. When the analysis was based on gender, the study discovered substantial variations in healthcare utilisation. Self-assessed health and chronic illness were the factors that determined how females used healthcare in the children's subsample. Education affected males' healthcare utilisation for the working class, whereas NHIS membership, obesity and physical inactivity determined females' healthcare usage. Lastly, chronic illness and diarrhoea influenced elderly males' healthcare utilisation, while NHIS membership, physical inactivity and locality (rural) affected the elderly females' utilisation.

The study recommends enhanced public education, especially among the working class, due to the positive effect of education on healthcare utilisation. Promotion of education among the male educated working class would have spillover effects on their dependents. In the design, planning and management of healthcare policies, an attempt should be made by policymakers to rope in the working class, especially the male gender, to minimise the consequences of delay in seeking care when ill. Finally, to eliminate the disparities in healthcare facilities between rural and urban dwellers, the government should improve healthcare services access for rural residents by establishing more Community-Based Health Planning and Services (CHPS) zones and other healthcare facilities in the rural areas to meet the healthcare needs of rural dwellers, particularly the elderly.

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Table A1. Predictors of NHIS membership or enrolment

Variable	Coefficient	p-value
Gender (male)	-0.405^{***} (0.024)	0.000
Age	0.003^{***} (0.001)	0.000
Education	0.064^{***} (0.017)	0.000
Married	-0.009 (0.028)	0.763
Household size	-0.014^{***} (0.005)	0.002
Obesity	0.101^{**} (0.041)	0.015
Self-assessed health	-0.070^{***} (0.023)	0.002
Chronic illness	-0.017 (0.028)	0.553
Physical inactivity	0.482^{***} (0.039)	0.000
Wealth index	-0.373^{***} (0.011)	0.000
Formal-sector work	0.625^{***} (0.050)	0.000
Savings	0.429^{***} (0.029)	0.000
Constant	0.091 (0.101)	0.369
Observations	31,807	
LR χ^2	$3{,}270.09^{***}$	
Log likelihood	-20,411.658	
Pseudo R^2	0.0742	
Model classification	63.68%	

Table A2: Second-stage regression results for visit to a health facility

Variable	Coefficient
NHIS membership	0.613^{***} (0.048)
Gender (male)	-0.324^{***} (0.048)
Education	0.147^{***} (0.028)
Obesity	0.207^{***} (0.064)
Self-assessed health	-0.757^{***} (0.031)
Chronic illness	0.496^{***} (0.049)
Physical inactivity	0.223^{***} (0.061)
Wealth index	-0.054^{***} (0.021)
Fever	1.993^{***} (0.075)
Cold or cough	1.721^{***} (0.144)
Diarrhoea	2.044^{***} (0.241)
Locality (rural)	-0.150^{***} (0.052)
Formal-sector work	-0.098 (0.081)
Constant	-0.403^{***} (0.131)
Observations	31,807
Wald χ^2	$2{,}564.76^{***}$
Log likelihood	-7,700.956
Pseudo R^2	0.1613
Model classification	91.64%

Notes: Bootstrapped standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$