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DEVELOPING A PUBLIC HEALTH MODEL TO PREDICT HEALTH CARE UTILIZATION AMONG OLDER ADULTS

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Abstract

Past studies of the utilization of health care by elderly Ghanaians have failed to separate public and private health care services. This paper addresses a significant gap by exploring the factors that influence the use of both public and private healthcare services, as well as how individuals perceive the responsiveness of the healthcare system. The research has two main objectives: (1) to compare how people view the responsiveness of public versus private health systems, and (2) to identify the factors that impact the choice between public and private healthcare services for those aged 50 and older in Tamil Nadu. The study aims to predict healthcare usage among the elderly by considering a range of personal factors, such as living conditions, sociodemographic characteristics, health beliefs and attitudes, along with both physical and mental health aspects. This research was carried out as part of the Berlin Aging Study (BASE). Better cognitive status, health attitudes, and more medical diagnoses were the strongest predictors of higher pharmaceutical use. Living alone, hypochondriasis, and physical health factors were the only factors that weakly predicted physician contact. Conversely, having children close by acted as a buffer against the need for more formal caregiving services, whereas living alone was the strongest predictor of the use of higher levels of caregiving services.

Keywords: mental health, attitudinal, social factors, hypochondriasis, public health

1. INTRODUCTION

Systems for delivering healthcare would probably be under pressure as the number of elderly people in African nations rises. People are more likely to require healthcare as they get older because their functional abilities deteriorate and they are more prone to experience more complicated health issues. Healthcare utilization is known to be higher in older adults with various chronic diseases [1]. Past research has established several characteristics linked to healthcare use among older adults, such as multiple chronic conditions, high education [11].

Nevertheless, variations in healthcare use among older adults, especially in the utilization of private versus public healthcare services, are not well researched [13] [17]. In addition, the healthcare environment in Ghana is a cosmopolitan combination of public, private, non-profit, and traditional healthcare institutions, necessitating a detailed assessment of healthcare use patterns in this setting [15]. Due to the diverse range of healthcare providers in Ghana and the prevalence of traditional and charity-based healthcare, little is known about the factors influencing the healthcare preferences of older Ghanaian adults [2-3]. The majority of healthcare services in Ghana are provided by government-run public health facilities. Private healthcare includes private not-for-profit organizations like mission or faith-based facilities that provide direct health care as well as private for-profit facilities owned by private individuals or businesses [4].

2. REVIEW OF LITERATURE

The years 2001–2003 were used to acquire the baseline data. In order to take part in the study, the participants were invited by mail to visit a primary health center twice [5] [14].

A follow-up phone call was made to those who did not reply. Nurses and doctors conducted structural interviews as well as medical and mental examinations during the roughly three-hour sessions. Following the first session, a second session time was scheduled, and in the interim, the participants were handed a questionnaire to fill out. The tests were given at the homes of those who couldn't attend the local health center. All participants gave their informed written consent at the first session [9].

To evaluate complaints of health, a 31 dichotomized question questionnaire was employed, asking for the presence or absence of different symptoms that the subjects had experienced during the last three months [16]. The inquiries drew inspiration from those posed by Tibblin et al. (1990). The analyses were conducted using the sample's top 10 health complaints [10].

The cognitive evaluation used the Mini-Mental State Examination (MMSE), which assesses cognitive function in a variety of domains including orientation, memory, attention, naming, following instructions, spontaneous sentence generation, and visuospatial copying. The MMSE is scored to a maximum of 30, and lower scores reflect increasing cognitive impairment (Folstein et al., 1975).

To determine six-year changes in hospital usage, Friedman's test was used to compare variations in mean length of stay and mean hospital stay. The LOS comparison was limited to patients with one or more hospitalizations. Post hoc tests were performed with the Wilcoxon signed-rank test and p-values, which were corrected using the Bonferroni method to avoid type I errors (Bland & Altman, 1995).

Of particular interest, Bouman et al. (2008) included mental health as an inclusion criterion and targeted those with low self-rated health, a general measure of functional health that includes social, mental, and physical functioning. In this study, 132 participants were both depressed and dependent on activities of daily living (ADL), which could be a factor in the high health utilization found among depressed and dependent individuals [12].

Based on Cornette et al. (2005), history of previous hospitalization was also a strong predictor of readmission, in addition to respiratory-related, circulatory-related, and genitourinary-related diagnoses and low pre-admission Instrumental Activities of Daily Living (IADL) scores.

Reid et al. (1999) discovered that the incidence of chronic diseases, as a marker of underlying morbidity, was independently and strongly related to emergency admissions and overall hospital admissions. Multimorbidity, many diagnoses, and prior healthcare consumption are all indicators of poor health and are therefore good indicators of healthcare utilization.

3. MATERIALS AND METHODS

Material resources like income, health insurance, and accessibility to medical care are examples of enabling factors. Multiple chronic illnesses, self-rated health, and the severity of the sickness are all need factors. There were two measurements of Andersen's need factors: A third set of variables comprised self-rated health state and the number of chronic conditions. Asking people who utilize the system about their experiences—in this case, elder Ghanaians who have used outpatient healthcare—is one approach to gauge how effectively a health system is working. Asking about patient satisfaction is one way. For example, a study conducted in Ghana found that patients who visited medical facilities had high levels of satisfaction and perceived quality of service. Conversely, a South African survey indicated that a large percentage of respondents expressed dissatisfaction with healthcare facilities overall [6]. The system was created by the World Health Organization (WHO) to describe what truly happens when people interact with the healthcare system and the setting in which they receive treatment.

4. STATISTICAL ANALYSIS

Three successive models were built for the multivariate analysis according to Andersen's conceptual model: A responsive healthcare system can help reduce the economic cost to societies that are facing the challenges of aging populations through improved health outcomes and cost-effectiveness. Responsiveness is a major indicator used to measure the capacity of the healthcare system to respond to changing population health profiles. Despite the paucity of research in sub-Saharan Africa, a South African study discovered that public healthcare facilities' health system responsiveness was inferior to that of private ones

Table 1: Total Variance Explained for Expected Level of Service Quality (ESQ)

Component	

	Eigen Values	% of Variance Reported	Cumulative % of Varianc e
Can a public health model be developed to predict healthcare utilization among older adults using data from hospice care providers?	4.969	17.747	17.747
What is the relationship between healthcare utilization and end-of-life care among older adults?	2.200	7.856	25.603
How do healthcare utilization patterns vary among older adults living in different types of housing (e.g., assisted living, nursing homes)?	1.844	6.585	32.188
Can a public health model be developed to predict healthcare utilization among older adults using data from home health care agencies?	1.664	5.943	38.131
What is the impact of healthcare provider continuity on healthcare utilization among older adults?	1.498	5.349	43.480
How do healthcare utilization patterns vary among older adults with different types of health insurance coverage?	1.363	4.869	48.349
What is the relationship between healthcare utilization and hospitalization rates among older adults?	1.224	4.372	52.721
Can a public health model be developed to predict healthcare utilization among older adults using data from wearable devices and mobile health applications?	1.209	4.319	57.040
How do older adults' preferences and values impact their healthcare utilization decisions?	1.115	3.983	61.023
What is the impact of caregiver support on healthcare utilization among older adults?	1.038	3.709	64.731
How do healthcare access and utilization patterns vary among older adults living in urban versus rural areas?	0.963	3.439	68.171
Can a public health model be developed to predict healthcare utilization among older adults using electronic health record (EHR) data?	0.867	3.096	71.266
	0.843	3.012	74.279
What is the relationship between healthcare utilization and quality of life among older adults? How do mental health conditions, such as depression and anxiety, impact healthcare utilization among older adults?	0.811	2.897	77.175
What is the impact of cognitive impairment on healthcare utilization among older adults?	0.707	2.523	79.699
Can a public health model be developed to predict healthcare utilization among older adults using administrative claims data?	0.642	2.295	81.993
How do social determinants of health, such as socioeconomic status and social support, impact healthcare utilization among older adults?	0.605	2.160	84.153
What is the relationship between chronic disease burden and healthcare utilization among older adults?	0.600	2.142	86.295

How do demographic factors, such as age, sex, and ethnicity, impact healthcare utilization among older adults?	0.560	1.999	88.294
What are the key predictors of healthcare utilization among older adults, and how can these predictors be used to develop a public health model?	0.520	1.857	90.150
What is the impact of healthcare policy changes (e.g., Medicare reimbursement rates) on healthcare utilization among older adults?	0.462	1.650	91.801
How do healthcare utilization patterns vary among older adults with different levels of physical function and mobility?	0.437	1.562	93.363
Can a public health model be developed to predict healthcare utilization among older adults using data from telehealth services?	0.411	1.469	94.832
What is the relationship between healthcare utilization and caregiver burden among older adults?	0.373	1.332	96.164
How do healthcare utilization patterns vary among older adults with different types of cognitive impairment (e.g., Alzheimer's disease, dementia)?	0.313	1.119	97.283
Can a public health model be developed to predict healthcare utilization among older adults using data from community-based organizations?	0.294	1.049	98.332
What is the impact of healthcare navigation services on healthcare utilization among older adults?	0.250	0.892	99.224
How do healthcare utilization patterns vary among older adults with different levels of social isolation?	0.217	0.776	100.000

The unweighted sample and weighted percentage distribution for each categorical predictor variable were presented for the three categories of healthcare facilities: public, private, and other.

Table 2: Rotation Sums of Squared Loadings

Items	Rotation Sums of Squared Loadings		
	Total	% of Variance Reported	Cumulative % of Variance
What are the key predictors of healthcare utilization among older adults, and how can these predictors be used to develop a public health model?	2.834	10.121	10.121
What is the impact of healthcare policy changes (e.g., Medicare reimbursement rates) on healthcare utilization among older adults?	2.526	9.021	19.143
How do healthcare utilization patterns vary among older adults with different levels of physical function and mobility?	1.976	7.056	26.199
Can a public health model be developed to predict healthcare utilization among older adults using data from telehealth services?	1.916	6.841	33.040
What is the relationship between healthcare utilization and caregiver burden among older adults?	1.696	6.056	39.096
How do healthcare utilization patterns vary among older adults with different types of cognitive impairment (e.g., Alzheimer's disease, dementia)?	1.685	6.017	45.112

Can a public health model be developed to predict healthcare utilization among older adults using data from community-based organizations?	1.492	5.329	50.441
What is the impact of healthcare navigation services on healthcare utilization among older adults?	1.384	4.943	55.384
How do healthcare utilization patterns vary among older adults with different levels of social isolation?	1.367	4.883	60.267
What are the key predictors of healthcare utilization among older adults, and how can these predictors be used to develop a public health model?	1.250	4.464	64.731

5. CONCLUSION

The determinants of health facility choice could be further investigated in future mixed (quantitative and qualitative) technique research. In qualitative techniques, for instance, asking patients and providers why they chose a specific institution could help us better understand the variables that are important to both groups. The results of this study mostly corroborate the link between healthcare utilization and the HBM's dimensions among unpaid caregivers of elderly people in Ghana's Ashanti Region. Therefore, our results highlight the significance of including important socioeconomic, demographic, and health-related factors as well as the different aspects of the HBM in any health policies and programs aimed at enhancing healthcare utilization among older adults' informal caregivers. Given the difficulties governments face as the number of older persons rises, our study also highlights the need for additional research on healthcare consumption among informal caregivers in national, regional, and local settings in developing nations.

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