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Nexus between Aging and Health Expenditure: An Evidence from Nepal

Tanka Mani Poudel[1], **Ram Prasad Gajurel**[1*]

[1]Mahindra Multiple Campus, Tribhuvan University, Dharan, Nepal

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**Corresponding email: gajurelrp@gmail.com*

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Abstract

Nepal, like many countries, is currently experiencing a significant shift in its demographic landscape, characterized by a rapidly aging population. This study investigates into the causal relationship between aging and healthcare expenditure in Nepal. To examine this causal connection, we employed a parsimonious VAR-based Wald test, Granger causality analysis, impulse response functions (IRFs), and forecast error variance decompositions using time series data from 2000 to 2020. The findings of the analysis reveal a substantial positive correlation between the proportion of elderly people and healthcare expenditure, indicating that as the population ages, healthcare costs and the demand for healthcare services tend to rise. The IRF analysis further confirmed that an innovation or shock in the aging index (AI) led to a subsequent increase in per capita health expenditure (HPC). Granger causality also reveals a unidirectional causal linkage from the aging index to per capita health expenditure. In addition, the study highlights the positive impact of aging on life expectancy in Nepal. These findings have important policy implications for Nepal. As the population continues to age, policymakers must allocate healthcare resources effectively, invest in geriatric care, and develop a robust healthcare infrastructure. Comprehensive long-term planning and strong social support systems are crucial to ensure the well-being of the elderly population and to mitigate the associated challenges.

Keywords: aging, health expenditure, life expectancy, parsimonious VAR, Granger causality, impulse response functions

Introduction

Since the latter half of the previous century, shifts in population demographics have resulted into an increasingly elderly population, which is now recognized as a significant global economic and social challenge. Recent time has witnessed a growing awareness regarding the connection between aging and healthcare expenses, as well as the broader social, economic, and political consequences of aging. The primary driving forces behind aging populations, as widely acknowledged, are extended life expectancies and reduced birth rates. Aging encompasses gradual and continuous changes in the human body. However, our perception of life's transitions, whether we embrace our maturity or lament physical decline, is heavily influenced by how our cultural framework defines the different life stages (Macionis, 2012).

Elderly people represent a category of population with specific interests and needs. Elderly people comprises a distinct demographic group with unique interests and requirements. Seniors face a variety of issues as a result of the aging population and various social and economic developments, which require an increasing amount of attention and assistance from social aides (Bodi, 2005).

As time progresses, the ages of individuals naturally change, while age differences refer to variations between different age groups. Distinguishing whether an observed outcome is due to an individual's aging process or disparities in age among groups can pose a challenge. Social gerontologists employ the idea of a cohort to aid in the identification of age differences. A cohort is an aggregate of individuals who experienced the same event within the same time interval (Ryder, 1965). Majority of researches make use of age cohorts, which are all people who were born into a population at the same time (Uhlenberg & Miner, 1996). But a cohort might also include individuals who enroll in a certain system at the same time. for instance, represent a cohort regardless of their age.

Ageing is a fact of life, and it has several social, political, and economic impacts as shown by our findings and the literature. The creation and execution of education, social, and employment programs for the elderly are crucial since many nations' populations are aging. In this particular context, the idea of distributing risk within health insurance and shifting risk from younger age groups to older ones might require prompt consideration. This complements the ongoing discussions surrounding the pension system, which has been a widely debated topic in recent years (Boz & Ozsar, 2019).

Ageing is a prominent feature of the global population in the twenty-first century. The development of technology, research, and medicine are necessary for the growing demographic and social changes to take place. Age-appropriate procedures for health promotion, prevention, treatment, and rehabilitation should be included in health systems (Medici, 2021). Due to improvements in the health sector and family planning techniques, population ageing is viewed as the outcome of a demographic shift from a high to low level of mortality, decreasing fertility rates associated with an increase in life expectancy (Bloom & Luca, 2016). The globe appears to be facing a significant difficulty in the future due to an aging population (Guerin et al., 2015). In contrast to the industrialized world, the aging population is increasing more quickly in developing countries. These rapidly increasing rates place a lot of pressure on emerging countries to swiftly modify national policies in order to meet the increasing needs of an aging population with limited resource bases (Bergman et al., 2013). The chronic diseases that require expensive treatments, such as diabetes, cardiovascular disease, chronic kidney disease, and cancer, are substantially more common in the aging population (WHO, 2011). All developing countries today are concerned about rising health care costs, which would be necessary to ensure older populations' good health (Mafauzy, 2000). Although social security offers a small level of protection for retirees, it was never intended to guarantee complete financial security. Instead, it serves as one of three stools, the other two being individual savings and pensions offered by companies. Only those who have employer pensions, personal savings, and some investments can typically continue to live as they did in retirement.

Nepal's demographic landscape has been evolved over the past few decades. Advances in healthcare, improvements in living conditions, and changes in social dynamics have contributed to a remarkable increase in life expectancy. This positive trend as shown in Figure 1, however, presents both opportunities and challenges, particularly in the realm of healthcare financing. The relationship between aging and health expenditure is a complex one, as the aging population tends to have distinct healthcare needs that can strain existing healthcare systems and resources. Healthcare expenditure has become a critical concern for policymakers in Nepal. As the population ages, the demand for healthcare services (Lopreite & Zhu, 2020) is likely to surge, potentially placing significant pressure on the healthcare infrastructure and expenditure.

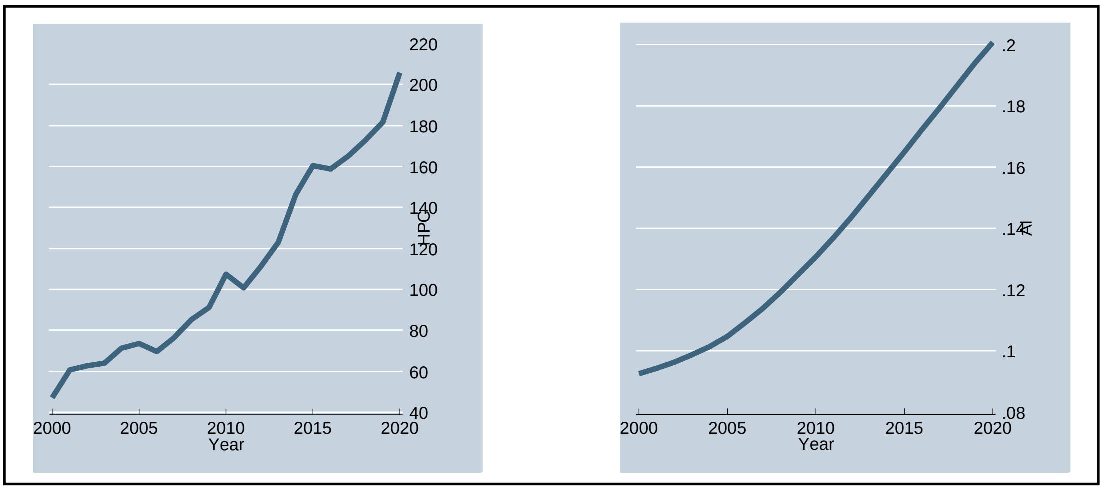
The aging population is a demographic phenomenon that is sweeping across the globe, with profound implications for various aspects of society, particularly in the realm of healthcare. Nepal experiences the increasing aging and health expenditure per capita as displayed in Figure 1. The nexus between aging and health expenditure is a multidimensional and dynamic phenomenon. It encompasses a complex array of factors that collectively influence healthcare utilization, costs, and quality for elderly individuals. By unraveling the causal nexus between aging and health expenditure, this research aspires to offer evidence-based insights that can inform healthcare policies and strategies tailored to Nepal's unique context. The findings have the potential to guide policymakers in making informed decisions that enhance the efficiency, equity, and sustainability of healthcare delivery as Nepal continues to navigate the challenges and opportunities presented by its aging population.

Aging presents a significant challenge in today's economy, contributing to increased demand for healthcare services and potentially impeding economic growth. In Nepal, the aging index is on an upward trajectory (Figure 1); however, the impact of this demographic shift on per capita health remains unexplored within the Nepali context. Existing literature offers a range of findings regarding the effects of aging on healthcare provision (HPC) and economic growth. Consequently, this study aims to address this research gap through an empirical investigation in Nepal, considering various interrelated variables. To examine the nexus between aging and health expenditure, this study employs the parsimonious VAR estimation and Granger causality. It is assumed that this framework with IRFs and forecast error variance decomposition might be helpful in assessing the causal linkage between aging and health expenditure in Nepal.

This research paper seeks to contribute to the existing body of knowledge by empirically investigating the causal relationship between aging and health expenditure in Nepal. Through a rigorous analysis of time-series data spanning from 2000 to 2020, this study aims to shed light on the causal connection between these variables. Furthermore, it considers the potential influence of other socio-economic factors, such as education levels, life expectancy, and economic growth, in shaping this relationship. Besides the introduction section, the paper is divided into a literature review, methodology, results and discussion, and conclusion and implication sections.

Figure 1

Trend of aging index (AI) and health expenditure per capita (HPC) ranging from 2000 to 2020.



Literature Review

Aging Perspective

Functionalists examine how society's components interact (Mohan, 2022). Functionalists assess how well society's components interact to maintain order in society. Functionalists discover that those with more resources who continue to be active in other spheres of life age more well (Crosnoe & Elder 2002). The disengagement theory contends that activity levels and social engagement are crucial to both this process and happiness. According to reformulated versions of this idea, hobbies and other informal activities are what have the biggest impact on later-life satisfaction (Cumming et al., 1961; Lemon et al., 1972). Continuity theory emphasizes the distinction between internal and external aging processes highlighting the role of personality in aging adaptation and the concept of ongoing adult growth. It suggests that older adults actively make choices to maintain consistency in their internal (for instance, personality and beliefs) and external (e.g., relationships) aspects while remaining engaged and active in their later years (Atchley 1971).

Modernization theory categorizes nations based on indicators like industrialization and urbanization, with those displaying modern social structures considered advanced (Neysmith, 1990). Holmes (1972) argues that industrialization and modernization erode the influence of the elderly, reducing their prestige and increasing social isolation. In pre-industrial societies, strict conventions required the younger generation to care for the elderly within extended families, but industrialization replaced this with nuclear families. As societies become more individualistic, caregiving for elders becomes voluntary and less socially enforced.

Interactionism, also known as symbolic interactionism, examines the subjective meaning of human interaction (Mohan, 2022). It explores how individuals in society interact in specific settings and emphasizes how these daily interactions shape society and influence how people perceive each other through cultural symbols. The subculture of aging theory, like the hypothesis of Rose (1962), is a micro-analytical theory that highlights the formation of a common community among excluded elderly individuals. According to this theory, seniors may withdraw from broader society and adopt new social behaviors that involve interactions with peers who share similar backgrounds and interests.

Nexus of Aging and Health Expenditure

Individual preferences and limitations shape older people's living arrangements (Reher & Requena, 2018). Health issues, functional capacity, finances, kin availability (like having a spouse or children), housing costs, and location (urban or rural) often lead to differences between preferred and actual living situations. Globally, aging populations are affected by broader social and economic shifts. Factors like declining fertility, changing marriage and cohabitation patterns, increased education levels among younger generations, rural-to-urban migration, and international migration are transforming the living environments of older individuals, impacting household size and composition (United Nations, 2020).

The issue of medical care for the elderly grows more pressing as medical technology advances lengthening the average American's life expectancy. Only 3.1 million Americans were 65 or older in 1900, making up just 4% of the nation's population. Today, however, approximately 38 million Americans, or 13% of the population, are 65 or older. Health and healthcare have been significantly impacted by this shift in the age distribution of the American population (Bureau of the Census, 2005). The global increase in older populations is a result of significant advancements, including lower fertility rates, reduced infant and maternal mortality, decreased infectious disease rates, and improved nutrition and education. This unprecedented growth is expected to continue, with the world's elderly population projected to exceed 1 billion by 2020, up from the current half a billion. Seniors are growing at a faster rate than the general population in most countries, particularly in China, India, the United States, and former Soviet Union nations, which together account for over half of the world's elderly population. China alone houses more than 20% of the world's total population (Tischler, 2011).

Elderly individuals typically have well-established social support networks, often characterized by a division of labor between family (providing instrumental support) and friends (offering emotional support) (Cornwell, 2011). These support networks are akin to lifelong investments, with deposits made early in life for withdrawals later on (Antonucci, 1985). While inheritance and biology play a role in chronic illness development, research underscores the significance of social factors. One's health lifestyle, encompassing choices like diet, exercise, personal hygiene, alcohol use, and safe practices, significantly impacts the likelihood of chronic diseases and impairments (Cockerham, 2011). Regular check-ups and adherence to prescribed treatments are additional health-related behaviors.

Many researches support the advantages of leading an active lifestyle. One study looked at the effects of physical activity on various mental health indicators in persons ages 20 to 64. In a study by Bielak et al. (2014), it was noted that individuals of various age groups who engaged in physical activity were more prone to sustain strong cognitive abilities and less likely to experience cognitive decline. Another research study found that individuals who maintained a regular exercise regimen exhibited improved cardiovascular health, enhanced cognitive function, and reduced disability compared to those who led a sedentary lifestyle (Middleton et al., 2010). Older individuals face heightened risks of income loss, depression, and mental health issues, especially without pensions, and experience increased isolation from family, friends, and communities. Physical separation can make them vulnerable to abuse, a concern highlighted during the pandemic. Many elderly living alone, especially the oldest, struggle to use technology, exacerbating their loneliness (United Nations, 2020).

An empirical study of Pakistan has shown that it faces increasing healthcare costs due to its shifting demographics. As the elderly population grows and chronic diseases become more common, the demand for healthcare services rises, impacting costs. This study, using 1995-2014 time-series data and Bayesian VAR analysis, found healthcare spending is more responsive to aging than GDP per capita or life expectancy. Healthcare costs increased by 2.6% due to aging and are projected to rise by 17.2% in a decade. Increasing life expectancy led to a 3.6% rise in healthcare spending per person, with a 14.2% increase expected in a decade. Real GDP per capita explained 1.7% and 3% of healthcare spending volatility (Shakoor et al., 2020).

The majority of studies (Borrescio-Higa & Valenzuela, 2021; Mason & Miller, 2018; Getzen, 1992; De Meijer et al., 2013; Bech, et al., 2011; Murthy & Okunade, 2016) support the notion that aging contributes to an increase in health expenditure. Moreover, many studies supported that there is as a causal linkage between aging and health expenditure (Boz & Ozsarı, 2020; Lopreite & Zhu, 2020; Lopreite & Mauro, 2017). Conversely, it is not supported and has no proper evidence from Korea (Hyun et al., 2016).

Methodology

Data and Variables of Interest

To examine the causal relationship between aging and health expenditure, we have considered annual time series data from 2000 to 2020 in this study. The dependent variable, health expenditure (HPC), is proxied by the current health expenditure per capita. The explanatory variable, aging, is proxied by the aging index (AI) following the methodology of Lopreite and Mauro (2017) and Lopreite and Zhu (2020). Additionally, drawing upon insights from various studies (Lopreite & Zhu, 2020; Boz & Ozsarı, 2020; Hyun et al., 2015; Shakoor et al., 2021), this study has also taken into account other variables that interplay in this context, including secondary level school enrollment (ENS), life expectancy (LE), and GDP per capita (GPC). The time series are obtained from the World Bank Indicators (WDI) (https://databank.worldbank.org/source/world-development-indicators). The description of all the variables of interest is presented in Table 1.

Table 1

Description of Proxies Variables

Variables	Proxies	Units of measurement	Descriptions	Source
Health expenditure	HPC	US dollars	Current health expenditure per capita with purchasing power parities (PPP) in current international dollars	WDI
Aging	AI	Index	Ratio of the total population aged 65 and above to the total population aged 0-14	WDI
Education	ENS	% gross	Secondary-level school enrollment	WDI
Life expectancy	LE	Years	Total years of life expectancy at birth	WDI
GDP per capita	GPC	US dollars	GDP per capita is measured in constant 2015	WDI

Note. GDP = Gross Domestic Product, WDI = World Development Indicators

Model Specification

For the causal connection between aging and health expenditure, basically, a causality approach with parsimonious VAR specification is employed. Reporting the results of impulse responses, forecasting error variance decompositions, and Granger-causality tests are standard procedures in VAR analysis (Stock & Watson, 2001). For the linear specification of the study, all the variables are transformed into logarithmic form. The linear model is specified as follows:

$$LnHPC_t = \beta_0 + \beta_1 LnAI_t + \beta_2 LnENS_t + \beta_3 LnLE_t + \beta_4 LnGPC_t + \varepsilon_t$$

Here, HPC_t represents the health expenditure per capita with purchasing power parities (PPP) in current international dollars. AI_t denotes the aging index, calculated as the ratio of the total population aged 65 and above to the total population aged 0-14. ENS_t is the percentage of gross secondary level school enrollment. LE_t stands for the total years of life expectancy at birth. GPC_t represents the GDP per capita in constant 2015 US dollars. ε_t is the error term capturing unexplained variations.

Before examining the causality, trend and description of data are evaluated. Thereafter, to ensure the stationarity of variables, the Augmented Dickey-Fuller (ADF) unit root test is carried out. The ADF test assesses the stationarity of a time series variable by regressing it on its own lagged values and a constant. The null hypothesis (H_0) of the ADF test is that the variable has a unit root ($\gamma = 0$), indicating non-stationarity, while the alternative hypothesis (H_1) is that the variable is stationary ($\gamma < 0$). The ADF unit root test equation for a single variable is as follows:

$$\Delta Y_t = \alpha_0 + \alpha_1 t + \gamma Y_{t-1} + \sum_{i=1}^{p} \beta_i \, \Delta Y_{t-i} + \varepsilon_t$$

Here, Y_t = observed time series, $\Delta Y_t = Y_{t-1} - Y_t$, α_0 = drift term or intercept, $\alpha_1 t$ = linear time trend, γ = test statistic for unit root, p = lag length, t = 1, 2, ….,T, i = 1, 2, …..n, $\sum_{i=1}^{p} \beta_i \, \Delta Y_{t-i} = \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \ldots + \beta_n \Delta Y_{t-p}$, and ε_t = error term.

In this paper to examine the causal linkage between AI and HPC, the Wald test based on parsimonious vector autoregressive (VAR) model is employed as followed by Kyara et al. (2021) for the causality between tourism and economic growth. Firstly, the standard VAR model is performed, then we eliminate the insignificant coefficient and perform Wald test (H_0: coefficient of VAR process = 0) to confirm the causal linkage between variables of interest. VAR model shows the dynamic interactions between variables. The p order VAR (p) model can be specified as (Lütkepohl, 2004)

$$y_t = A_1 y_{t-1} + \ldots\ldots + A_p y_{t-p} + u_t$$

where $A_1, A_2, \ldots\ldots A_p$ = (K×K) coeffect matrices, y_t = variables of time series = $(y_{1t},\ldots,y_{kt})'$, and u_t = unobservable error term = $(u_{1t}, \ldots\ldots, u_{kt})'$.

To determine the direction of causality, the Granger (1988) is performed that precisely estimates the pairwise lag effect on the current period of time series. The basic Granger causality between, for instance, HPC and AI, is specified as:

$$LNHPC_t=\sum_{j=1}^{p} A_{11,j} LNHPC_{t-j}+\sum_{j=1}^{p} A_{12,j} LNAI_{t-j}+\varepsilon_t$$
$$LNAI_t=\sum_{j=1}^{p} A_{21,j} LNAI_{t-j}+\sum_{j=1}^{p} A_{22,j} LNHPC_{t-j}+ u_t$$

The matrix form of the above Granger causality specification is

$$\begin{bmatrix} LNHPC_t \\ LNAI_t \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} LNHPC_{t-1} \\ LNAI_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} A_{11,j} & A_{12,j} \\ A_{21,j} & A_{22,j} \end{bmatrix} \begin{bmatrix} LNHPC_{t-j} \\ LNAI_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ u_t \end{bmatrix}$$

where α and β are the intercept of the above Granger specification.

In this paper's final analysis, we use impulse response functions (IRFs) to investigate the short-term and long-term cause-and-effect dynamics between AI and HPC by observing how HPC responds when a one-unit innovation or shock is applied to AI. Breitung (2004) states that if we have an estimator $\hat{\theta}$ for the VAR coefficients summarized in the vector θ, we can derive estimators for the impulse response as functions of $\hat{\theta}$. The arbitrary impulse response coefficient, denoted as $\phi = \phi(\theta)$ can be expressed as $\hat{\phi} = \phi(\hat{\theta})$.

Given the limited number of observations and variables, applying more complex dynamic models to the study within the context of Nepal may not be appropriate. The results and discussions obtained using these methods are presented in the following section.

Results

Descriptive Summary

These statistics collectively provide insights into the characteristics of each variable, helping to understand their central tendencies, variability, symmetry, and adherence to normality in the dataset of 21-year observations for each variable (Table 2).

Table 2

Statistical Summary

	HPC	AI	ENS	GPC	LE
Mean	111.1369	0.136743	58.24589	750.4152	66.64938
Median	100.8125	0.130756	57.63132	726.0553	66.81400
Maximum	205.8840	0.200552	85.52149	1061.486	69.55800
Minimum	47.18504	0.092583	35.76190	546.9316	62.61400
Std. Dev.	47.47221	0.035538	14.68958	166.5902	2.075298
Skewness	0.476061	0.369942	0.267336	0.436530	-0.466933
Kurtosis	1.900858	1.796509	1.871436	1.909333	2.174413
Jarque-Bera	1.850318	1.746340	1.364588	1.707815	1.359485
Probability	0.396468	0.417625	0.505456	0.425748	0.506747
Observations	21	21	21	21	21

Note. HPE = health expenses per capita, AI = aging index, ENS = enrollment in secondary level, GPC = GDP per capita, LE = life expectancy.

In a 21-year data set analysis, all examined variables, including Health Expenses per Capita (HPC), Aging Index (AI), Enrollment in Secondary Level (ENS), GDP per Capita (GPC), and Life Expectancy (LE), exhibit characteristics consistent with normal distribution. HPC's mean is around 111.14 units, with positive skewness (0.48) and moderate kurtosis (1.90), yet the Jarque-Bera test ($p = 0.40$) suggests normality. AI, with a mean of 0.14, shows positive skewness (0.37), kurtosis (1.80), and a Jarque-Bera test ($p = 0.42$) supporting normality. ENS, GPC, and LE also display similar characteristics and pass Jarque-Bera tests with p-values ranging from 0.43 to 0.51. Thus, all variables in this 21-year dataset appear to follow normal distributions.

Unit Root Test

To confirm the stationarity of series, several unit root tests are performed. The pre-evaluation of the series shows that series are upward trending as shown in Figure 1 and insights into the non-stationarity of the series. To reach a conclusion, the ADF unit root test is carried out. The results of ADF unit root test are presented in the Table 3.

Table 3

Unit Root ADF Test Results

	Level			First different		
	With Constant	With Constant & Trend	Without Constant & Trend	With Constant	With Constant & Trend	Without Constant & Trend
LNHPC	-0.756	-3.186	4.227	-5.5672***	-5.3037***	-3.3737***
LNAI	-3.076**	-1.757	-2.079**	-1.5921	-1.9646	-1.2605
LNENS	-0.807	-3.785**	4.418	-4.2626***	-4.0948**	-2.6017**
LNGPC	0.1811	-3.919**	5.219	-3.0216*	-4.0096**	0.7806
LNLE	-2.127	-2.285	3.601		-6.0963***	-6.7061***

Note. (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. Null Hypothesis: the variable has a unit root. Probability based on MacKinnon (1996) one-sided p-values

The Augmented Dickey-Fuller (ADF) test results reveal the stationarity properties of several time series variables under different model specifications. At the level, most variables, including LNHPC, LNAI, and LNENS, fail to reject the null hypothesis of having a unit root, indicating non-stationarity. However, when tested with the first difference, the majority of these variables exhibit statistical significance, suggesting that they become stationary after differencing once. Notably, LNHPC and LNENS show particularly strong evidence of stationarity in their first differences. In contrast, LNGPC appears stationary at the level with or without a constant but not with a constant and trend, while LNLE is non-stationary at the level but stationary in its first difference. These results imply that the variables are likely integrated of order one (I(1)), but they become stationary when differenced once, making them suitable for time series analysis. Thus, the results confirm that there is mixed order of stationary of variables of interest.

Selection of Optimal Lags

To examine the sound connection among variables of interest, optimal lag has to be estimated correctly. There are several criteria to select optimal lag, out of them Akaike information criterion (AIC) and Schwarz information criterion (SIC) are quite popular. The minimum value of AIC and SCI are rule of choosing optimal lag. The VAR (2) optimal lag length criteria are presented in Tabel 4.

Table 4

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	187.9593	NA	2.98e-15	-19.25888	-19.01034	-19.21681
1	279.6800	125.5126	2.96e-18	-26.28211	-24.79089	-26.02974
2	327.2297	40.04183*	5.60e-19*	-28.65576*	-25.92186*	-28.19307*

Note. * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQ: Hannan-Quinn information criterion. Endogenous variables: LNHPC LNAI LNENS LNGPC LNLE

Among the different lag orders considered, lag 2 is indicated as the most appropriate choice by various criteria, as denoted by asterisks (*). Overall, these criteria including AIC, SIC and HQ collectively suggest with their minimum values that a lag 2 VAR model is the most suitable choice for modeling the data.

Estimation of Parsimonious VAR Model

After choosing optimal lag 2, the unrestricted or standard VAR model is performed with 2 lags. The result of VAR is not take into account the study. This paper tries to examine the causal nexus among the variables of interest. The overall VAR estimations to confirm the lag, the results are presented in Table 5.

Table 5

VAR Estimate

Determinant resid covariance (dof adj.)	5.71E-20
Determinant resid covariance	7.56E-22
Log likelihood	327.2297
Akaike information criterion	-28.65576
Schwarz criterion	-25.92186

The VAR estimates of Table 5 indicate AIC has lowest value than SIC. Thus, AIC criteria for lag length is the best criteria and it suggests that optimal lag is 2 as SIC.

Tabel 6

Results of Parsimonious VAR Model

	Coefficient	**Std. Error**	**t-Statistic**	**Prob.**
C(3)	1.634882	0.045973	35.56169	0.0000
C(11)	7.999994	0.094534	84.62519	0.0000
C(14)	1.958166	0.048723	40.18965	0.0000
C(15)	-0.968226	0.049945	-19.38574	0.0000
C(22)	-0.018248	0.005467	-3.337879	0.0013
C(25)	0.954764	0.036414	26.21951	0.0000
C(33)	6.006773	0.074879	80.22021	0.0000
C(37)	1.616774	0.226103	7.150595	0.0000
C(41)	-0.876123	0.271128	-3.231396	0.0018
C(44)	15.71119	2.244423	7.000102	0.0000
C(46)	0.044966	0.013421	3.350471	0.0012
C(51)	-0.057554	0.028398	-2.026663	0.0459
C(54)	0.682455	0.122158	5.586656	0.0000
C(55)	1.517017	0.433753	3.497423	0.0008
Determinant residual covariance		1.22E-20		
Equation: LNHPC = C(3)*LNAI(-1)+ C(11)				
Observations: 20				
R-squared	0.985966	Mean dependent var		4.661169
Adjusted R-squared	0.985187	S.D. dependent var		0.405437
S.E. of regression	0.049346	Sum squared resid		0.043830
Durbin-Watson stat	1.562658			
Equation: LNAI = C(14)*LNAI(-1) + C(15)*LNAI(-2) + C(22)				
Observations: 19				
R-squared	0.999963	Mean dependent var		-1.984708
Adjusted R-squared	0.999958	S.D. dependent var		0.242964
S.E. of regression	0.001572	Sum squared resid		3.95E-05
Durbin-Watson stat	1.416742			
Equation: LNENS = C(25)*LNAI(-1) + C(33)				
Observations: 20				
R-squared	0.974485	Mean dependent var		4.056913
Adjusted R-squared	0.973067	S.D. dependent var		0.238164
S.E. of regression	0.039086	Sum squared resid		0.027498
Durbin-Watson stat	1.290636			
Equation: LNGPC = C(37)*LNAI(-2) + C(41)*LNGPC(-2) + C(44)				
Observations: 19				

R-squared	0.994540	Mean dependent var	6.626956
Adjusted R-squared	0.993858	S.D. dependent var	0.208413
S.E. of regression	0.016334	Sum squared resid	0.004269
Durbin-Watson stat	2.302683		
Equation: LNLE = C(46)*LNHPC(-2) + C(51)*LNGPC(-1) + C(54)*LNLE(-2) + C(55)			
Observations: 19			
R-squared	0.972682	Mean dependent var	4.204901
Adjusted R-squared	0.967218	S.D. dependent var	0.026496
S.E. of regression	0.004797	Sum squared resid	0.000345
Durbin-Watson stat	2.339062		

The estimated VAR (2) model indicates that none of the coefficients for the variables are statistically significant. This suggests the possibility of an issue with excessive lags affecting the estimation of the regressors' effects on the dependent variables. To investigate this further, we have conducted a Wald test within a more parsimonious VAR framework, with the null hypothesis being that non-significant coefficients are equal to zero. Surprisingly, the Wald test provides support for the null hypothesis. Given that the presence of several non-significant coefficients can lead to overparameterization in this estimation model, we have removed these coefficients and re-estimated the parsimonious VAR. The results of this re-estimation are presented in Table 5. The Wald test of re-estimated coefficient with null hypothesis, H_0 : C(3) = C(11) = C(14) = C(15) = C(22) = C(25) = C(33) = C(37) = C(41) = C(44) = C(46) = C(51) = C(54) = C(55) = 0, also confirms the significant different of coefficient from zero. The re-estimated parsimonious VAR equations as Table 6 are as follows:

Equation 1: LNHPC = C(3)*LNAI(-1)+ C(11)

Equation 2: LNAI = C(14)*LNAI(-1) + C(15)*LNAI(-2) + C(22)

Equation 3: LNENS = C(25)*LNAI(-1) + C(33)

Equation 4: LNGPC = C(37)*LNAI(-2) + C(41)*LNGPC(-2) + C(44)

Equation 5: LNLE = C(46)*LNHPC(-2) + C(51)*LNGPC(-1) + C(54)*LNLE(-2) + C(55)

The results of the parsimonious Vector Autoregression (VAR) model reveal essential insights in the relationship among the variables. Let's delve into the coefficients and their relationships in each equation. Equation 1 examines the effect of AI on HPC. The coefficient for LNAI(-1) is 1.635, indicating that a one percent increase in lagged LNAI leads to an estimated 1.635 percent increase in LNHPC in the current period, all else being equal. This positive coefficient suggests a strong positive relationship between AI and HPC as consistent with Lopreite & Zhu (2020), Boz & Ozsarı (2020) and Shakoor et al. (2021). The increase in health expenditure associated with aging can be attributed to a combination of factors, including the growing burden of age-related health conditions, rising healthcare costs, and the social and economic complexities of caring for an aging population. Equation 2 implies the relationship of AI and its lagged value. In this equation, the coefficient for previous year LNAI terms C(14) is positive, suggesting that pervious year aging also rising the current aging. However, AI with second lag is negative with current AI. The causes behind the observed relationship in Equation 2 may be multifaceted, potentially influenced by factors such as the cumulative impact of aging over time and more distant AI trends might offset the current AI impact.

Equation 3 implies that previous year AI has positive impact on current year ENS. Older individuals often encourage younger people to enroll in educational programs, citing the positive influence of aging as it creates opportunities for them to pursue further education or career changes. Equation 4 shows that the lagged AI variable has a positive effect, while the lagged GPC variable has a negative impact on the current GPC, suggesting that aging from two years ago contributed to an increase in GDP per capita, but the GDP per capita from the same time frame negatively influences the current GDP per capita. Similarly, equation 5 implies lagged of HPC and LE positively influenced the current LE. Conversely, lagged GPC is negatively associated with current LE.

Wald coefficient diagnostic for causality, pairwise Granger causality, impulse response functions (IRFs) and forecast error variance decomposition

The Wald coefficient diagnostic with re-specified parsimonious VAR model is utilized to examine the causal relationships among the variables of interest. To do this, we set the null hypothesis as H_0: C(3) = C(11) = C(14) = C(15) = C(22) = C(25) = C(33) = C(37) = C(41) = C(44) = C(46) = C(51) = C(54) = C(55) and perform the Wald coefficient diagnostic. The results of the Wald test are presented in Table 7. The significant Chi-square statistic from the Wald test confirms the existence of a causal connection between C(3), C(14), C(15), C(25), C(37), C(41), C(46), C(51), C(54), and the dependent variable (HPC). In this context, C(3) represents the coefficient of AI, indicating a causal relationship between AI and HPC as consistent with Boz and Ozsarı (2020) and Lopreite and Zhu (2020).

Table 7

Results of Wald Coefficient Diagnostic

Test Statistic	**Value**	**df**			**Probability**
Chi-square	10267094	13			0.0000
Null Hypothesis: C(3)=C(11)=C(14)=C(15)=C(22)=C(25)=C(33)=C(37)=C(41)=C(44)=C(46)=C(51)=C(54)=C(55)					
Null Hypothesis Summary:					
Normalized Restriction (= 0)	**Value**	**Std. Err.**	**Normalized Restriction (= 0)**	**Value**	**Std. Err.**
C(3) - C(55)	0.117865	0.436182	C(37) - C(55)	0.099757	0.489146
C(11) - C(55)	6.482977	0.443935	C(41) - C(55)	-2.393140	0.511519
C(14) - C(55)	0.441149	0.436481	C(44) - C(55)	14.19418	2.285952
C(15) - C(55)	-2.485243	0.436619	C(46) - C(55)	-1.472051	0.428538
C(22) - C(55)	-1.535265	0.433787	C(51) - C(55)	-1.574571	0.429001
C(25) - C(55)	-0.562253	0.435279	C(54) - C(55)	-0.834562	0.552777
C(33) - C(55)	4.489756	0.440168			

The causal connection is also confirmed by a diagnostic test – the residual normality test. The normality test, with the null hypothesis that residuals are multivariate normal, is accepted by all of the components, both individually and jointly with Kurtosis, as shown in Table 8. Thus, it confirms the robustness of the causal estimation in this study.

Table 8

Results of System Residual Normality Tests: Cholesky (Lutkepohl) Orthogonalization

Component	**Skewness**	**Chi-sq**	**df**	**Prob.**
1	0.583761	1.135924	1	0.2865
2	0.832412	2.309700	1	0.1286
3	-0.611656	1.247075	1	0.2641
4	1.241710	5.139480	1	0.0234
5	-0.999019	3.326798	1	0.0682
Joint		**13.15898**	**5**	**0.0219**
Component	Kurtosis	Chi-sq	df	Prob.
1	2.382755	0.317492	1	0.5731

2	4.166293	1.133534	1	0.2870
3	2.339607	0.363433	1	0.5466
4	5.379387	4.717903	1	0.0299
5	3.383116	0.122315	1	0.7265
Joint		**6.654677**	**5**	**0.2476**
Component	Jarque-Bera	df	Prob.	
1	1.453417	2	0.4835	
2	3.443233	2	0.1788	
3	1.610508	2	0.4470	
4	9.857383	2	0.0072	
5	3.449113	2	0.1783	
Joint	**19.81365**	**10**	**0.0311**	

On the other hand, pair wise Granger causality with a lag of 2 is performed to examine bidirectional causality between the variables of interest. In these tests, the null hypothesis posits that one variable does not Granger cause the other. The results as presented in Table 9 indicate that LNAI Granger causes LNHPC at nearly a 1% significance level, suggesting that past values of AI unidirectionally influence HPC. Conversely, LNHPC does not Granger cause LNAI. Similarly, LNHPC Granger causes LNLE at a 5% significance level, indicating a unidirectional causal connection between HPC and LE. Furthermore, there is a unidirectional causal connection from AI to ENS, AI to GPC, GPC to ENS, and LE to GPC. Thus, the overall findings reveal that there is a causal connection from AI to HPC, AI causes ENS and GPC, HPC causes LE, and LE causes GPC. Consequently, aging causes an increase in health expenditure, but eventually, it improves life expectancy, as well as the standard of living and income of the individual.

Table 9

Pairwise Granger Causality Tests

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**	**Causality**
LNAI $\xrightarrow{Gr}$ LNHPC	19	6.34631	0.0109	Unidirectional: AI → HPC
LNHPC $\xrightarrow{Gr}$ LNAI		0.72840	0.5001	No causality
LNENS $\xrightarrow{Gr}$ LNHPC	19	2.44780	0.1226	No causality
LNHPC $\xrightarrow{Gr}$ LNENS		1.94420	0.1798	No causality
LNGPC $\xrightarrow{Gr}$ LNHPC	19	2.60197	0.1094	No causality
LNHPC $\xrightarrow{Gr}$ LNGPC		2.23526	0.1437	No causality
LNLE $\xrightarrow{Gr}$ LNHPC	19	2.05749	0.1647	No causality
LNHPC $\xrightarrow{Gr}$ LNLE		4.34413	0.0341	Unidirectional: HPC → HLE
LNENS $\xrightarrow{Gr}$ LNAI	19	1.13057	0.3506	No causality
LNAI $\xrightarrow{Gr}$ LNENS		6.48727	0.0101	Unidirectional: AI → ENS
LNGPC $\xrightarrow{Gr}$ LNAI	19	0.07418	0.9289	No causality
LNAI $\xrightarrow{Gr}$ LNGPC		17.2824	0.0002	Unidirectional: AI → GPC
LNLE $\xrightarrow{Gr}$ LNAI	19	1.77636	0.2053	No causality
LNAI $\xrightarrow{Gr}$ LNLE		0.26858	0.7683	No causality
LNGPC $\xrightarrow{Gr}$ LNENS	19	5.15847	0.0210	Unidirectional: GPC → ENS

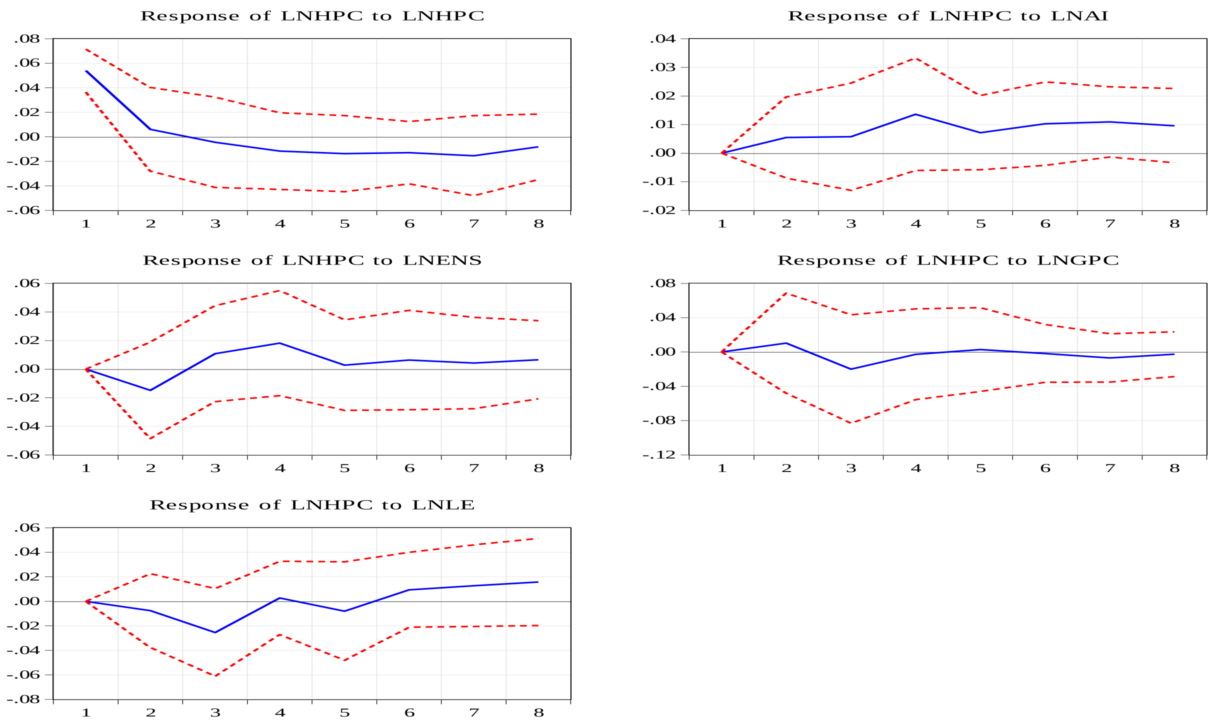
LNENS $\xrightarrow{Gr}$ LNGPC		1.60485	0.2358	No causality
LNLE $\xrightarrow{Gr}$ LNENS	19	0.65328	0.5355	No causality
LNENS $\xrightarrow{Gr}$ LNLE		1.23490	0.3207	No causality
LNLE $\xrightarrow{Gr}$ LNGPC	19	3.46948	0.0597	Unidirectional: LE → GPC
LNGPC $\xrightarrow{Gr}$ LNLE		1.74881	0.2099	No causality

The insights provided by Impulse Response Functions (IRF) go beyond mere causality. They estimate how variables respond to shocks in different periods when given shocks in other variables. To confirm the existence of causal connections, IRF provides additional evidence. Figure 2 displays the IRF illustrating how HPC responds to shocks or innovations in the explanatory variables. The lower and upper dashed lines represent the 95% confidence interval. The IRF plot depicts the response to Cholesky one standard deviation (SD) innovations, plus or minus the standard error. In this plot, we observe the response of HPC when a one standard deviation shock or innovation is given to the variables of interest.

The IRF reveals that one-unit standard deviation (SD) innovation or shock given to HPC itself causes a decreasing effect on HPC, which continues up to period 2, after which it steadily decreases further. Similarly, one SD shock on AI elicits a positive response from HPC. This finding aligns with the causality results indicating that AI leads to a gradual increase in HPC in the short run and a constant increase in the long run. Additionally, a one SD innovation to ENS results in a fluctuating response from HPC. Initially, it decreases HPC, then it rises for up to 4 periods, followed by a subsequent reduction, although it remains increased compared to the baseline. Likewise, any shock on GPC causes a short-term rise in HPC, followed by a decrease. Finally, a one-period SD innovation on LE leads to a reduction in HPC for up to 5 periods, with fluctuations, after which HPC gradually rises in the long run.

Figure 2

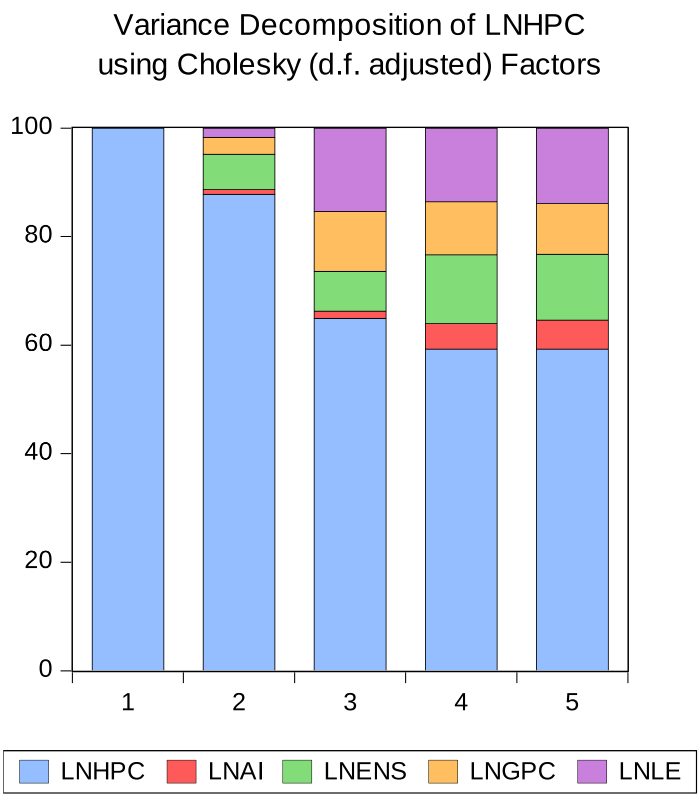
Impulse Response Function for Response of HPC



Forecast error variance decomposition analysis helps to understand how much each variable contributes to the forecast errors at different points in time shedding light on the relative importance of these variables in forecasting LNHPC. The Figure 3 shows the results of a forecast error variance decomposition of LNHPC.

Figure 3

Forecast Error Variance Decompositions of LNHPC from the Recursive VAR Ordered as LNHPC, LNAI, LNENS, LNGPC, LNLE



In the short run (period 1), LNHPC is entirely responsible for the forecast errors, contributing 100% to the variance. However, in subsequent periods, other variables come into play. However, in long run, the smaller percentage of forest error variance in LNHPC is explained by any fluctuation in itself, which was 59.26% in fifth period. By the second period, LNHPC still has the largest influence, but LNAI, LNGPC, and LNLE also contribute to the changes in LNHPC in long run. As we move further into the forecast, the contributions of these variables become more pronounced, particularly LNLE, which becomes a significant factor. The overall results reveal that life expectancy can contribute more to health expenditure. However, increasing percentage of forecast error variance of LNAI reveals that aging may contribute significantly to health expenditure in the long run.

Conclusion

The study investigates the nexus between aging and health expenditure using annual time series data from Nepal spanning the years 2000 to 2020. The parsimonious VAR based Wald test and Granger causality as well as impulse response function (IRF) and forecast error variance decompositions (FEVD) are employed. The preliminary findings indicate that AI and HPC are trending upward. The Wald coefficient diagnostic under parsimonious VAR and Granger causality tests provided robust evidence of a causal relationship between aging (AI) and health expenditure (HPC). Aging is found to significantly influence health expenditure, with past values of AI unidirectionally affecting current health expenditure. IRF also confirms that one unit innovation or shock on AI rises the HPC. FEDV also reveals that AI is significantly influenced the HPC in long-run. This finding is consistent with prior research and underscores the increasing healthcare burden associated with an aging population. The VAR modeling demonstrates intricate interactions between aging, health expenditure, education (ENS), GDP per capita (GPC), and life expectancy (LE). These interactions highlight the multifaceted nature of the relationships in the context of Nepal. Our analysis reveals that aging positively affects secondary-level school enrollment (ENS) and GDP per capita (GPC), while education and GDP per capita are found to impact life expectancy (LE). These findings suggest that as the population ages, there may be positive spillover effects on education and economic growth, contributing to improved living standards. Thus, overall findings reveal that the health expenditure of Nepal is significantly influenced by the rising gaining in Nepal.

This study's findings have significant implications for healthcare policy and planning in Nepal. As the population ages, policymakers should prepare for increased healthcare demand, manage rising health expenditures, and promote the benefits of an aging workforce. Long-term planning should include investments in healthcare infrastructure and support systems for the elderly, mitigating challenges associated with an aging demographic.

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