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Long Run Analysis between Climate Change, Socio-Economic Factors and Technology on Health Expenditure in Malaysia

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Abstract

Environmental sustainability is one of the most important agendas for a country to focus on, making societies and communities balanced and defensible. Healthy and pleasant surroundings create better production and economic growth. Many researchers have found that climate change is one of the most significant contributors to environmental destruction produced by humanity. Climate change affects the overall health of a nation. People may suffer skin irritation due to air pollution, diarrhea due to water pollution, and other symptoms. This empirical study uses an ARDL approach to explore the possibility of estimating the short and long-term impacts of climate change, socio-economic factors, and technology on health expenditure in Malaysia. The research found that GDP, birth rate, and technology significantly reduce health expenditure. In contrast, climate change and inflation increased long-term health expenditure in Malaysia. The results were superior to those of the previous study, as shown by the comprehensiveness of the ecological footprint in measuring climate change. This study may increase awareness among people and industry players about reducing ecological waste. Environmental policy should be intensified, and investment in healthcare technology should be empowered to increase human capital and reduce economic costs. This will enable the government to focus on other types of expenditure for the country's development.

Keywords: climate change, health expenditure, socio-economic, technology

1. Introduction

Based on the Grey System Theory, total health expenditure was influenced by nine hot topics in the economy, population, health service utilization, and policy (Jia et al., 2021). The scholars forecast the determinants of health expenditure and found different relationships among the variables because the methods and fundamentals used were varied. Health is a crucial determinant of human capital. Thus, excellent health can significantly enhance output and contribute to economic progress (Yang, 2020). Besides education and lifestyle, the environmental conditions of a country can represent one of the health status factors (Akintunde et al., 2019). In Malaysia, water pollution is a severe environmental problem (Khalil et al., 2011). Water pollution harms the sustainability of water resources, plants, organisms, populations, and the economy (Afroz & Rahman, 2017). Malaysia is currently becoming a developing country, which has led to an increase in contemporary lifestyles, air, water, and soil pollution. The continuous discharge of chemical contaminants and global climate change presents additional threats to environmental health. These variables contribute to communicable and non-communicable illnesses and physiological and neurological problems. According to a survey carried out by IPSOS (2019), 45% of respondents stated that climate change was the worst environmental issue in Malaysia. People are concerned and realize the effects of climate change on their health and daily lives.

Climate change poses immediate and significant threats to our community and future generations. Climate change is an unavoidable reality in many developing nations, and it is the primary cause of pollution and an increase in the likelihood of having poor health. Furthermore, inadequate access to clean water can lead to diarrhea (Hardy et al., 2019), typhoid fever (Stanaway et al., 2017), and cholera (Hardy et al., 2019). Additionally, deforestation causes the spread of disease-causing vectors such as malaria, resulting in increased health costs (Olson et al., 2020). These concerns will eventually increase potential healthcare costs if they are not appropriately mitigated and improved. Long-term exposure to air pollution can harm people's respiratory systems, infant mortality, life expectancy (Chen et al., 2013) and cause sleeping issues (Heyes & Zhu, 2019). All these undesirable consequences impact economic expenses. Resultantly, the higher the levels of climate change, the higher the financial consequence faced by the government.

Recently, various studies have used ecological footprint (EFP) to quantify pollution or climate change using a wide range of air, water, and soil chemicals, as an alternative to carbon dioxide (CO2). EFP was applied as a proxy for environmental degradation (Gillani et al., 2021; Yang & Uthman, 2021; Ahmad et al., 2020; Hassan et al., 2019). CO2 is no longer an appropriate metric since it only monitors gas emissions contributing to global warming. In contrast, EFP investigates the use of productive surface areas such as agriculture, grazing space, fishing grounds, developed land, forest area, and carbon demand on land. Thus, EFP is a critical component to understanding the implications of climate change on the ecosystem that subsequently affects civilization (Destek & Sarkodie, 2019).

On the other hand, several previous studies focused on the relationship between CO2 emissions, Gross Domestic Product (GDP), and health spending, while several researchers have studied the link between economic growth and environmental quality using the Environmental Kuznets Curve (EKC) (Cai et al., 2018; Pata, 2018). Additionally, the relationship between health spending and GDP was also analysed (Gövdeli, 2019; Rana et al., 2020). Economists estimated the elasticity of income to identify the nature of health care services and subsequently forecasted the healthcare demand and divided healthcare resources among areas based on the income elasticity determined. Lastly, the relationship between CO2 emissions and healthcare spending was also investigated. Several studies focused on the one-way causation from CO2 emissions on health expenditure and have found a positive relationship (Wang et al., 2019). According to Geng et al. (2019), various scholars have performed empirical investigations of the long-term effects of air pollution at the national level. Air pollution can raise healthcare costs by disrupting socioeconomic patterns, thus increasing the demand for healthcare services. Based on data provided by the United Nations Environment Program (UNEP) in 2016, the financial impact of outdoor environmental pollution in developing countries amounts to approximately 5% of their GDP. The empirical models produced by the UNEP captured the link between health and energy use in the industrial, commercial, and urbanization processes.

Several Malaysian researchers have investigated the economic determinants of health expenditure (Rahman, 2011; Eneji et al., 2013; Kim & Lane, 2013; Boachie & Ramu, 2017), yet there is limited local data on the impact of climate change on health expenditure. Consequently, to the best of our knowledge, this study is a pioneering attempt to address a vacuum in the current literature on the relationship between climate change, socioeconomic factors, and technology in terms of health expenses in Malaysia. Resultantly, this study aims to: (1) investigate the effects of climate change, socioeconomic factors, and technology on health expenditure, and (2) use the Autoregressive Distributed Lag (ARDL) cointegration method to investigate climate change, socioeconomics, and the technology nexus in Malaysia from 1970 to 2017.

This study contributes to the concept of health spending by considering climate change, socioeconomic issues, and technology as contributing elements to EFP. Existing research on health expenditure is rapidly increasing; however, limited studies have incorporated the primary factors in their equation model, resulting in inconsistencies. Furthermore, this study aims to expand a previous study (Abdullah et al., 2016) by employing a longer time series data span from 1970 to 2017 with various proxies in the equation model, such as EFP and technological advancement. Accordingly, the result from this study will further enhance the knowledge of Malaysia's health expenditure. Even with limited samples, the use of ARDL cointegration error-correction modeling is relatively consistent and can describe both short-run and long-run correlations. Furthermore, the ARDL bounds testing have excellent statistical power and nominal size distortion even in small samples (Murthy & Okunade, 2016).

These findings can help to increase awareness about the relationship between climate change and economic costs. Furthermore, educating people on saving energy, decreasing pollution, and managing solid waste is critical in reducing health issues and healthcare costs. The government can then utilize or redirect healthcare spending to alternative expenditures to help achieve higher economic growth and better social development.

This study comprises five sections: Section two summarises the current literature review, and Section 3 describes the data and methodology employed. Additionally, Section 4 delves into the findings and discussion, while Section 5 provides policy implications and a conclusion to the study.

2. Literature Review

2.1 Health Expenditure and Climate Change

Malaysia is a high human-development country that needs additional allocation to develop healthcare essentials. Health expenditure is required to improve well-being and EFP (Lenzen et al., 2020). Consequently, environmental policies are needed to reduce the primary cause of concern in nations: pollution and climate change. Both pollution and climate change are comprehensive measures of human strain on the environment (Ansari et al., 2021).

Lately, EFP has emerged as a critical environmental indicator used. The website of Global Footprint Network (https://www.footprintnetwork.org/our-work/ecological-footprint/) defines EFP as total land and water required to sustain a population with a particular lifestyle and technology while absorbing all wastes and emissions. The EFP is an excellent indicator of a population's resource demand against the available natural resources becoming increasingly valuable throughout the global economy. Moreover, EFP assesses the long-term viability of existing human activities and contributes to public awareness and decision-making (Yang et al., 2021).

The Global Footprint Network website recorded that Malaysia has an EFP of 3.9 global hectares per capita compared to the globe's entire biocapacity in 2019. Malaysia is ranked 35th globally in terms of EFP gha (global hectares) per capita and has a larger EFP than the worldwide (https://worldpopulationreview.com/country-rankings/ecological-footprint-by-country).

Previously, researchers measured the connection between environmental deterioration and health spending using CO2, Nitrogen dioxide (NO2), and Sulphur dioxide (SO2) as proxies for ecological degradation. For instance, Yazdi et al. (2014) examined the relationship between environmental quality and public health expenditure using CO2 and SO2 in Iran and found that CO2 and SO2 levels are substantial and positively connected to public health spending. Furthermore, Abdullah et al. (2016) included NO2 as a new variable for environmental quality assessment. Using the ARDL method, the study discovered that public health spending was affected by NO2 positively and significantly. Both Fattahi (2015) and Apergis et al. (2020) employed panel data analysis to compare the different income groups across countries and discovered that CO2 is positively connected to health spending.

The national health spending was divided into two categories: public and private. The causal relationship between environmental quality and both public and private healthcare expenditure in 15 Economic Community of West States (ECOWAS) countries was investigated using the Generalised Method of Moments (GMM) system, fixed effects, and pooled Ordinary Least Squares (OLS) from 1995 to 2014 (Alimi et al., 2020). The study inferred that carbon emissions had a statistically significant positive effect on public and national healthcare spending, similar to Yahaya et al. (2016) 's finding on 125 developing countries. Conversely, this study found no relationship between private healthcare expenditure and environmental pollution.

A fixed-effect model, a random-effect model, and a Panel Threshold Regression Model was utilized by Shen et al. (2021) to explore the existence of a threshold impact of industrial air pollution on medical expenses in Eastern, Central, and Western China. According to the results, severe air pollution increases medical costs in Eastern and Central China, and the effect of the central region on air pollution is greater than that of the eastern region. Nevertheless, in Western China, there is a non-linear threshold effect between the two variables. Additionally, air pollution lowers healthcare expenditures before the critical value but rises after the critical value. Nevertheless, the enhanced value is inadequate to offset the adverse effects of air pollution. In conclusion, most research implies that environmental quality increases health spending, yet some argue that the two variables have a statistically insignificant connection. This varied result is contributed by different estimating methods or variable of interest proxies.

2.2 Health Expenditure and Socio-Economic Factors

Healthcare investment may result in additional health opportunities, boosting human capital and productivity, which lead to economic success. Consequently, it is critical to examine a country's healthcare expenditure. Characteristically, the amount of money spent on health is proportionate to the country's income or GDP. The bigger the GDP of a country, the greater the healthcare spending (World Health Organisation, 2015). The majority of research postulated a significant relationship between health expenditure and national income (see Boussalem et al., 2014; Fazaeli et al., 2015; Zaman et al., 2017; Wang et al., 2019; Raghupathi & Raghupathi, 2019). According to Boussalem et al. (2014), there is a long-run relationship between public health expenditure and economic growth based on annual statistics from 1974 to 2014 in Algeria.

Moreover, the result indicates that health-related reform had minimal impacts on development but would still benefit the country. According to Fazaeli et al. (2015), there is a causal relationship between components and a long-run equilibrium between health expenditure and GDP in 12 Organisation of Petroleum Exporting Countries (OPEC). Using STATA to investigate the association between total health expenditure and GDP in Bangladesh, Zaman et al. (2017) found that GDP positively influences healthcare expenditure. Similarly, Wang et al. (2019) had found a long-run relationship among health expenditure, CO2 emissions, and GDP in the Netherlands, New Zealand, and the USA over the period 1975–2017. In the case of the USA, Raghupathi and Raghupathi (2020) postulated a significant positive association between healthcare expenditure and economic variables such as income, GDP, and labor productivity from 2003 to 2014. The positive relationship between health expenditure and GDP is basically found among the western developing countries. Eastern country such as China has a low fraction of GDP dedicated to healthcare due to other priorities such as infrastructure (Chen et al., 2020).

In terms of inflation, Vinod (2020) revealed that Malaysia's healthcare costs are among the highest in Asia compared to countries such as China, India, Indonesia, Japan, the Philippines, Singapore, South Korea, Taiwan, Thailand, and Vietnam. The result was based on the Aon Head of Wellbeing Solutions survey, which postulated that the aging population and the incidence of non-communicable diseases (NCDs) add to the complexity of treatment, leading to increase hospital expenses. Moreover, Malaysians prefer to obtain treatment from specialists rather than general practitioners for essential medical services, increasing healthcare costs. In their study on the determinants of public health care spending in Zimbabwe, Dhoro et al. (2011) discovered that the inflation rate negatively influences public health care spending. Similarly, Pakdaman et al. (2019) found a negative connection between inflation and health spending in Iran. However, the cointegration analysis was applied by Turgut et al. (2017) to investigate the link between Turkish health spending and inflation and discovered a statistically positive relationship between the variables establishing that inflation may increase the price of healthcare products.

In Pakistan, a study found that health expenditures were negatively influenced by crude birth rate (CBR) and other variables using multivariate approaches (Yaqoob et al., 2018). As health expenditures rise, the crude birth rate declines. Similarly, Boachie et al. (2014) utilized the cointegration analysis to investigate the drivers of health expenditure in Ghana and observed that the CBR was positively correlated to health expenditure. Given Ghana's high population expansion, the government's healthcare budget must be increased to sustain an efficient healthcare system. Consequently, government initiatives, such as free maternity care, which may increase the number of births per 1000 people, would increase healthcare expenditures significantly.

In contrast, Magazzino and Mele (2012) inferred that the CBR did not impact health expenses in Italy. They used Panel techniques using state-level data to evaluate the drivers of health spending from 1980 to 2009. The findings indicated that the birth rate could not account for the region's health expenditure. The different analyses may provide different interaction results between health expenditure and birth rate population among the nations.

2.3 Health Expenditure and Technological Progress

Medical progress has expanded the scope of treatments, diagnostics, and the development of specific medical equipment that can reduce surgery and healing time for patients. Several researchers claim that medical progress is one of the determinants of health expenditure. Different proxies are used, such as human capital (Frogner, 2010), time effect (Narayan et al., 2011; Ke et al., 2011; Farag et al., 2012), health sector research and development (R&D) funding (Murthy & Ketenci, 2017; You & Okunade, 2017), the mortality rate (MR) (Barkat et al., 2019), life expectancy, death rate, pharmaceutical R&D (Colombier, 2012), and patent numbers (Wong, 2012).

It is challenging to track suitable measures of technological progress in the health sector; therefore, Columbier (2012) used the MR as a proxy to measure technological progress and discovered a negative relationship with health expenditure. This study postulated that technological advancement should improve health outcomes, such as increasing life expectancy, reducing infant mortality, decreasing death rates, and reducing healing time. Similarly, Marino and Lorenzoni (2019) assessed the quality gained by the technology and explained that it positively impacts health outcomes such as life expectancy and aging populations. The technology is useful and beneficial not only to the healthcare system but also to patients.

3. Data and Methodology

3.1 Data

This study utilized data from 1970 to 2017, which included variables such as health expenditure per capita (HEPC), real GDP per capita (GDPPC), EFP, birth rate (BR), INFLA, and MR. Given the different units of measurement, the data is converted into natural algorithms to induce the stationary process (Murthy & Okunade, 2016), reduce the possibility of autocorrelation and heteroscedasticity (Rana, Alam & Gow, 2020), and provide reliable empirical results by decreasing data sharpness (Barati & Fariditavana, 2020). Table 1 summarises the data description and sources, whereas Figure 1 illustrates the time plots of the variables analyzed in the study.

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Table 1. Variable Descriptions and Source

Variable	**Code**	**Description**	**Source**
Health expenditure	HEPC	Health expenditure per capita (RM million)	Department of Statistic Malaysia
GDP	GDPPC	GDP per capita (US$)	World Bank
Ecological footprint	EFPPC	Ecological footprint (EFP) global hectares per capita	Global Footprint Network
Birth rate	BR	Birth rate, crude (per 1,000 people)	World Bank
Inflation rate	INFLA	Inflation, consumer prices (annual %)	World Bank
Mortality rate	MR	Mortality rate (per 1000 live birth)	World Bank

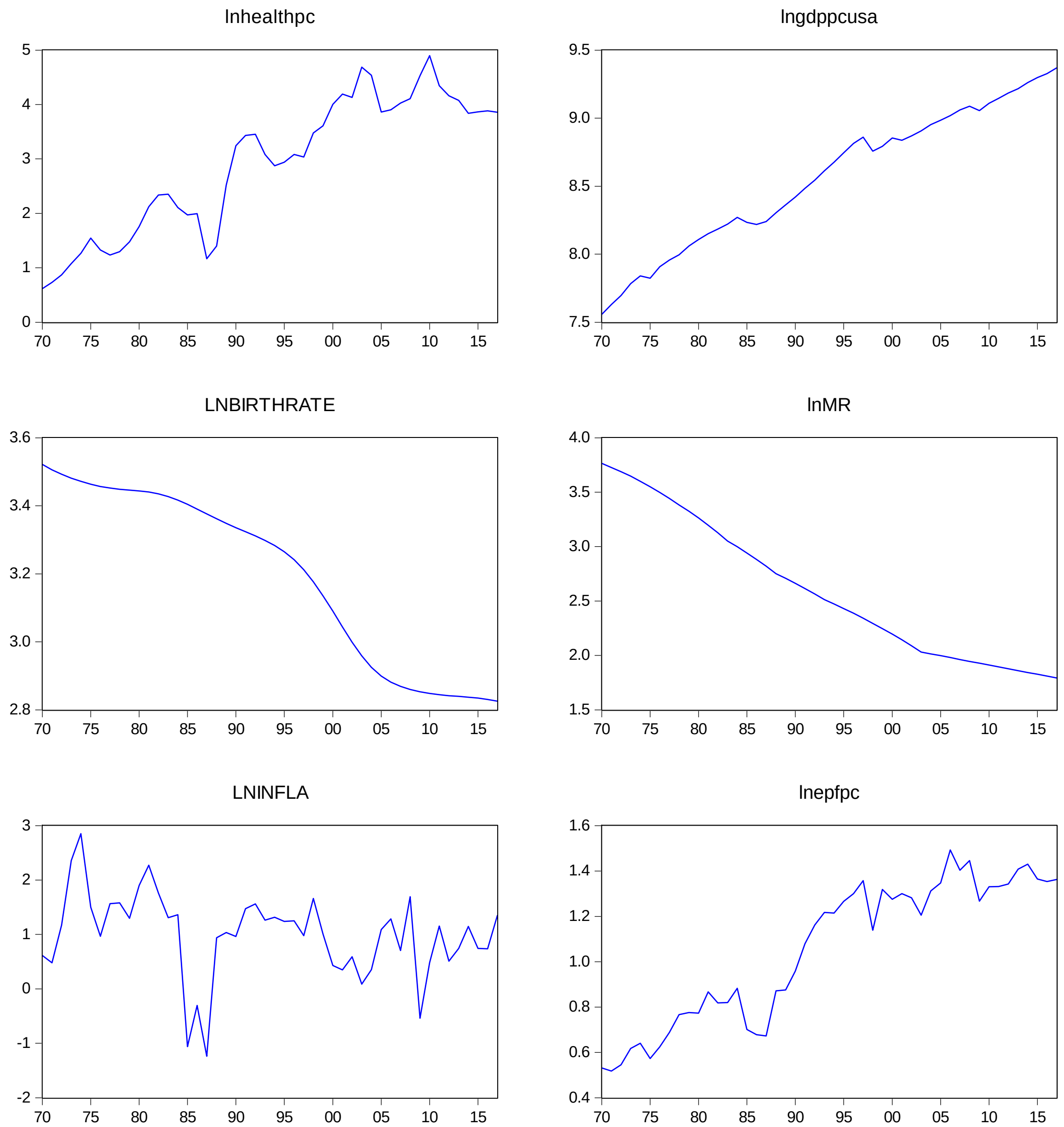

Figure 1. The trend of the data series where lnhealthpc, lngdppcusa, lnbirthrate, lnmr, lninfla, and lnefppc represents natural logarithm of health per capita, real gdp per capita, birth rate, mortality rate, inflation, and ecological footprint, respectively

3.2 Model

The econometric model in this study followed Abdullah et al. (2016), who investigated the relationship between health expenditures, air carbon emissions, and socioeconomic factors. This study focuses on environmental pollution rather than air carbon emissions to determine the link between health and EFP utilising the equation (1) below:

$$HEPC_t = f\,(GDPPC_t,\ EFPPC_t,\ BR_t,\ INFLA_t,\ MR_t) \qquad [1]$$

Specifically, *t* indicates the period of observation from 1970 to 2017, the HEPC represents the health expenditure per capita, the RGDPPC is an income proxied by the real GDP per capita, EFPPC represents the climate change proxied by the ecological footprint (EFP), BR (birth rate) is the annual number of births per 1000 population, INFLA represents the inflation rate of consumer prices annually (%) which is included to represent the influence of macroeconomic stability on the economy (at a rate of 1%). Additionally, the MR is a measure of technical advancement based on the mortality rate per 1,000 live births.

Equation (2) was converted into a linear logarithmic quadratic parameter using natural logs (ln) to provide a reasonable interpretation (Barati & Fariditavana, 2020) and expressed as follows:

$$\ln HEPC_t = \alpha + \beta_1 \ln RGDPPC_t + \beta_2 \ln EFPPC_t + \beta_3 \ln BR_t + \beta_4 \ln INFLA_t + \beta_5 \ln MR_t + \varepsilon_t \qquad [2]$$

Specifically, α is the intercept, εt is the error term, and the parameters β1 – β5 denote the estimated coefficients.

3.3. Methodology

This study estimated five critical econometric phases. The first phase is a unit root test breakpoint (Perron,1990), followed by the ARDL bound test by Murthy and Okunade (2016) to establish the existence of cointegration among the variables. Furthermore, the ARCH test, Breusch-Godfrey test, Jarque-Berra test, Ramsey-regression equation specification error test (RESET), cumulative sum (CUSUM), and CUSUM of squares (CUSUMSQ) tests are used in the third phase. The ARCH test was employed to determine the presence of heteroscedasticity. Furthermore, the Breusch-Godfrey test determined the serial correlation, while the Jarque-Berra test determined the normalcy. The fourth econometric phase employed the modified OLS (Philips and Hensen, 1990) and dynamic OLS cointegration tests to validate the robustness. Lastly, the fifth phase utilized a variance decomposition analysis and an impulse response function inside a Vector Autoregression (VAR) framework (Huarng & Yu, 2015) to forecast the degree of the causal effect of the determinants beyond the sample period.

3.3.1 Unit Root Test.

Before utilizing ARDL, a unit root test was performed to prevent misleading regression results by verifying variable stationarity (Murthy & Okunade, 2016). Various time-series empirical studies, such as Murthy (2012), Tajudeen et al. (2018), and Wang et al. (2018), have used the breakpoint unit root test to determine the presence of structural change in a time series. Consequently, trend-stationary data in the face of a structural break will provide a false null result. This null result is due to the structural change and unit-roots similarity. A unit root test was also carried out to determine the best technique for the next econometrics operation depending on the order of integration of the variables. The unit root test was carried out by assessing the stationarity condition of each variable (Murthy & Okunade, 2016).

3.3.2 Cointegration Test.

The ARDL process was applied by Pesaran & Smith (1995), and Pesaran et al. (2001) used to investigate the cointegration among variables. The cointegration method used the integration order of the variables, such as I (1), I (0), or a combination of the two to estimate the variables in long-run or short-run models. The ARDL approach was applied as this method produces. It is advantageous to use the relatively robust findings even when all the variables are endogenous (Khandelwal, 2015) or have a small sample size (Magazzino & Mele, 2012; Murthy & Okunade, 2016). An ARDL representation was constructed from equation (3) to estimate the variables' cointegration, yielding the following equation (4), which displayed the unconstrained error correction model (UECM):

$$\Delta \mathrm{lnHEPC}_t = \alpha + \sum_{i=1}^{q} \beta_{1i}\ \Delta\mathrm{lnHEPC}_{t-1} + \sum_{i=0}^{q} \beta_{2i}\Delta\mathrm{lnRGDPPC}_{t-i} + \sum_{i=0}^{q} \beta_{3i}\ \Delta\mathrm{lnEFPPC}_{t-i} + \sum_{i=0}^{q} \beta_{4i}\ \Delta\mathrm{lnBR}_{t-i} + \sum_{i=0}^{q} \beta_{5i}\ \Delta\mathrm{lnINFLA}_{t-i} + \sum_{i=0}^{q} \beta_{6i}\ \Delta\mathrm{lnM}R_{t-i} + \beta_7\,\mathrm{lnHEPC}_{t-1} + \beta_8\,\mathrm{lnRGDPPC}_{t-1} + \beta_9\,\mathrm{lnEFPPC}_{t-1} + \beta_{10}\,\mathrm{lnBR}_{t-1} + \beta_{11}\,\mathrm{lnINFLA}_{t-1} + \beta_{12}\,\mathrm{lnM}R_{t-1} + \varepsilon_t \qquad [3]$$

The β1−β6 are the coefficients for the short-run whereas β7−β12 are the coefficients used for the long-run. This study applied the Wald statistic as a single cointegration test to analyse the significance of the relationships among the variables. The equation below represents the null hypothesis of no cointegration among variables.

$$(H0: \beta7=\beta8=\beta9=\beta10=\beta11=\beta12=0) \text{ versus the alternative hypothesis of}$$
$$(H_1= \beta7\neq\beta8\neq\beta9\neq\beta10\neq\beta11\neq\beta12\neq 0) \qquad [4]$$

The regression of a small sample was validated by Narayan (2005) by comparing the F-statistic generated by the UECM and the crucial F-statistic values. If the F-statistic derived from limits testing surpasses the higher critical values indicated by Narayan (2005), the null hypothesis was rejected, and the variables' cointegration will be verified. Nevertheless, the null hypothesis cannot be rejected if the F-statistic does not exceed the lower critical values. If the F-statistic results were between the upper and lower critical levels, the analysis was not conclusive. Following the cointegration of the variables, the estimation for the long-term model was given below:

$$\Delta \mathrm{lnHEPC}_t = \alpha + \sum_{i=1}^{q} \beta_{1i}\ \Delta\mathrm{lnHEPC}_{t-i} + \sum_{i=0}^{q} \beta_{2i}\Delta\mathrm{lnRGDPPC}_{t-i} + \sum_{i=0}^{q} \beta_{3i}\ \Delta\mathrm{lnEFPPC}_{t-i} + \sum_{i=0}^{q} \beta_{4i}\ \Delta\mathrm{lnBR}_{t-i} + \sum_{i=0}^{q} \beta_{5i}\ \Delta\mathrm{lnINFLA}_{t-i} + \sum_{i=0}^{q} \beta_{6i}\ \Delta\mathrm{lnM}R_{t-I} + \mathcal{E}_t \qquad [5]$$

Next, the short-run coefficients were computed using the ARDL technique and the error correction model (ECM):

$$\Delta \ln HEPC_t = \alpha + \sum_{i=1}^{q} \beta_{1i}\ \Delta \ln HEPC_{t-1} + \sum_{i=0}^{q} \beta_{2i} \Delta \ln RGDPPC_{t-i} + \sum_{i=0}^{q} \beta_{3i}\ \Delta \ln EFPPC_{t-i} + \sum_{i=0}^{q} \beta_{4i}\ \Delta \ln BR_{t-i} + \sum_{i=0}^{q} \beta_{5i}\ \Delta \ln INFLA_{t-i} + \sum_{i=0}^{q} \beta_{6i}\ \Delta \ln MR_{t-I} + \varnothing ECT_{t-1} + \varepsilon_t \qquad [6]$$

The ECT_{t-1} represented the delayed error correction term, and $\varnothing$ was the error correction term coefficient that determined the adjustment speed. For the error correction process to work, the error correction term coefficient must be considered negative. The ECT indicated that a longer time was taken to adjust from short-run shock to long-run levels.

3.3.3 Diagnostic and Stability Test.

To prevent the model from having parameter bias, being ineffective, and producing an incorrect hypothesis, the error term εt in the estimated model must have a normal distribution, a constant mean of zero value and variance, no autocorrelation, homoscedasticity, and no multicollinearity (Murthy & Okunade, 2016). Consequently, the ARCH, Breusch-Godfrey, and Jarque-Berra tests were executed. The Ramsey-RESET test was utilised to ensure that the model was operational (Khandelwal, V. (2015). Furthermore, the CUSUM and CUSUMQ analyses were employed to assess the model stability, which is considered stable at a significance level of 5%. The test plots that exceed this critical limit are more likely to suffer a structural break throughout the estimated period (Murthy & Okunade, 2016).

3.3.4 Fully Modified OLS, Dynamic OLS, and Canonical Cointegration Regression for Robustness Check.

This study utilized a fully modified OLS, dynamic OLS, and Canonical Cointegration Regression to test robustness, as Philips and Hensen (1990) described. The dynamic OLS parametric approach was created to address issues, such as bias in small samples, serial correlation, and endogeneity (Magazzino & Mele, 2012). This entails the regression of a dependent variable with the lead, lag, and level of an independent variable. The Canonical Cointegration Regression is similar to FMOLS, where stationary data transformations are employed to obtain least squares estimates. Consequently, the long-run reliance between the cointegrating equation and stochastic regressor innovations was eliminated (Mujtaba & Shahzad, 2021).

3.3.5 Variance Decomposition Analysis and Impulse Response Analysis.

The impulse response analysis was used to identify the shock effect between variables (Matthew, Osabohie, Fasina,& Fasina, 2018). The impulse response function indicates the length and extent to which variables respond to external shocks from other variables (Lopreite & Zhu, 2020). This study employed variance decomposition analysis to estimate the reaction of changes from one variable to another and illustrate the importance of an independent variable's causal influence on a dependent variable and vice versa. The causal effect is based on the dependent variable's prediction error variance percentage (Dinçer & Yuksel, 2019).

4. Findings and Discussion

The results of the breakpoint unit root test are shown in Table 2. The breakpoint unit root was used to assess the variables' stationarity (see Table 2). The integration order of one or zero (I(1), I(0)), or both were predetermined before the ARDL test was carried out to ensure proper operation. The results indicate that all the variables are stationary at a first-order integration or I(1). These results support the use of ARDL as an approximated method for identifying a long-run connection between variables. Additionally, the ARDL bound test was applied to equation (6) to test for cointegration among the variables after the I(2) was identified, as suggested by Khandelwal (2015).

Table 2. Breakpoint Unit Root Test

Variable	**At Level**				**At First Difference**			
	Constant		**Constant and Trend**		**Constant**		**Constant and Trend**	
	TBs	t-Statistic	TBs	t-Statistic	TBs	t-Statistic	TBs	t-Statistic
LnHEPC	1987	-3.8284 (4)	2010	-5.1738(3)**	1987	-6.3156(3)***	1987	-5.9097***(6)
LnRGDPPC	1988	-2.8247(0)	2007	-3.9131(8)	1998	-7.4088(0)***	1998	-7.3197(0)***
LnEFPPC	1987	-4.5249(1)**	1990	-4.4307(0)	1998	-9.4558(0)***	1998	-9.3347(0)***
LnBR	1994	-4.1551(6)	1994	--4.6611(6)*	1994	-4.9347(13)***	2008	-6.2533(4)***
LnINFLA	1985	-4.9847(0)***	1987	-5.0333(0)**	1987	-5.3700(4)***	1987	-5.6118(4)***
LnMR	2003	-3.1996(6)	2003	-3.4842(5)	2003	-5.3177(5)***	2003	-6.3230(5)***

*, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively. The maximum amount of lag was set to 9. The breakpoint was chosen using the Dickey-Fuller min-t technique, the lag length was chosen using the Schwarz criteria, and the optimum lag is stated in brackets.

The optimal lag duration results are shown in Table 3.

Table 3. Lag Order Selection Criteria

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	58.69561	NA	3.67e-09	-2.395255	-2.151956	-2.305028
1	420.9698	609.2793	1.35e-15	-17.22590	-15.52281	-16.59431
2	547.4505	178.2229	2.43e-17	-21.33866	-18.17578	-20.16571
3	650.3991	116.9869	1.49e-18	-24.38178	-19.75910*	-22.66747
4	718.3782	58.70929*	6.09e-19*	-25.83537*	-19.75291	-23.57970*

* Indicates lag order selected by the criterion

The AIC and three additional criteria (FPE, SC, HQ) all indicate that a lag of four is ideal, where the value of each criterion was reduced. The AIC was employed in this experiment with a four-second lag time, and the bound test was carried out based on the results of the lag-length test. The F-statistic values are indicated in Table 4.

Table 4. Bounds Testing for Long-run Relationship

k=5 lnHEPC │ lnGDPPC, lnEPFPC, lnBR, lnINFLA, lnMR		
F-statistics	18.0775***	
Critical Value		
Narayan (2005)	I(0)	I(1)
1%	3.41	4.68
5%	2.62	3.79
10%	2.26	3.35

*, ** and *** represents significance at 10%, 5% and 1% level respectively.

Table 4 indicates the estimated F-statistic (18.0775) results compared to the bottom and upper limits of the results by Narayan (2005). Conversely, the estimated F-statistic was more than the 1% upper limit critical value, indicating a long-run cointegration link between public health spending, income, EFP release, birth rate, inflation rate, and death rate. After evidence of cointegration had been identified, the long-run and short-run regressions were performed using equations (5) and (6), respectively. Table 5 indicates the findings of the long-run regression, whereas Table 6 indicates the results of short-run regression.

Table 5. Long-Run Results of ARDL Model Estimation

Long-run estimation results (4,4,4,1,4,0)		
lnHEPC │ lnEPFPC, lnBR, lnRGDPPC, lnINFLA, lnMR		
Variable	**Coefficient**	**t-statictic**
LnRGDPPC	-6.2857***	-6.7162
lnEPFPC	4.0325***	4.4895
lnBR	-3.721963***	-3.0134
LnINFLA	0.264152**	2.1526
LnMR	-3.917815***	-5.8973
Diagnostic Tests	F-statistics	p-value
BG-LM	2.1877	0.1391
Breusch-Pagan-Godfrey	25.1706	0.6694
Jarque-Bera	0.5750	0.7501
Ramsey-RESET	2.0688	0.1740

*, ** and *** represents significance at 10%, 5% and 1% level respectively.

Based on Table 5, the ARDL estimate demonstrates that real GDP per capita lowered the public health expenditure due to the negative long-run significant association with HealthPC.

A 1% rise in real GDP per capita lowered public health spending by 6.29%. In addition, these findings were comparable to Chen et al. (2021), who determined the macro-level efficiency of health spending of 15 nations. They observed that several nations, such as China, India, and the Russian Federation, had a lower ideal proportion of GDP spent on health. Even as GDP rises, healthcare expenditure falls on average as the governments prefer to spend more on other priorities, such as infrastructure in China.

Several studies denote a relationship between GDP and health expenditure (Abdullah et al., 2016; Apergis, Bhattacharya & Hadhri,2020) which contradicts the results of this study. In Malaysia, healthcare allocations are increasing annually. In 2011, 7.3% of the total government expenditure was allocated to healthcare, increasing to 9.3% in 2018. Nonetheless, healthcare spending as a proportion of GDP has been relatively constant over the previous decade. In 2011, the allocation for healthcare which included both development and operational costs was 2.4% of the GDP. In addition, healthcare accounted for only 2.2% of the GDP in 2021. According to the World Bank, the healthcare expenditure of the Malaysian government is lower than the average of 3.84% of the GDP among upper middle-income nations up to 2018. It is worth noting that government healthcare spending as a proportion of the GDP varies greatly across upper-middle-income nations, with the greatest at 15.21% and the lowest at 0.59% in 2018.

The average government healthcare expenditure in high-income nations was 5.23% of the GDP. Government healthcare spending varies significantly, particularly in upper-middle-income nations, ranging from 1.36% to 9.2% of the GDP. According to a study titled "Global Spending on Health 2020: Weathering the Storm" by the World Health Organisation (WHO), there is no apparent relationship between income and the proportion of healthcare spending in any income category. Each country's policy decisions determine the health-financing system and variances in epidemiological tendencies.

Climate change has been postulated to significantly and positively correlated to public health expenditure. An increase of 1% in climate change increased the government health expenditure by 4.03%. This finding is consistent with other scholars who define pollution as an environmental degradation where air pollution is likely to stimulate government spending (Boachie et al., 2014; Odusanya et al., 2014; Chen et al., 2011). Moreover, EFP represents climate change issues since it is comprehensive and includes waste from the air, forest, land, and aquatic environments. EFP is used as a proxy for climate change and tracks the number of natural resources consumed by humans. Additionally, environmental degradation causes infection, skin radiation, diarrhea, and death. Malaysia is making strenuous efforts to decrease pollution and produce a sustainable environment with an estimated RM 1835 million, or 68.1% of the overall cost allocated towards pollution management (Department of Statistic Malaysia, 2019).

The birth rate and technological progress show a significant and negative effect on public health expenditure. A 1% increase in birth rate and technological progress decreased the health expenditure by 3.72% and 3.92%, respectively. Similarly, Yaqoob et al. (2018) corroborated that birth rate influences health expenditure. Conversely, this study indicates that Pakistan's birth rate and health expenditures are the opposite. Similarly, the mortality rate also has a negative relationship with health expenditure. Similar results were obtained by David (2018) and Barker et al. (2021). In addition, the advancement of medical technology can help increase life expectancy and overall health, reducing the need for health care.

Concurrently, the INFLA shows a significant positive correlation with health expenditure. As the INFLA increases by 1%, the public health expenditure also increases by 0.26%. This result indicates that the value of healthcare costs in monetary terms is stable or increasing as inflation increases prices.

Malaysians have a proclivity towards living longer lives. According to the Malaysian Department of Statistics (DOSM), the average life expectancy at birth in 2018 was 75 years. Due to the rise in life expectancy, Malaysians usually have sufficient insurance or any long-term insurance policy throughout their lifespan. Based on the Aon worldwide poll on the medical trend rate, the average global medical rate for 2018 was 8.4%, whereas the average general INFLA was 3.1%. Nonetheless, it was highlighted that Malaysia's medical trend rate was 15.3%, which was the second-highest in Asia. Since 2016, the cost of medical care in Malaysia has risen steadily. In 2017, the medical care cost increased from 11.8% to 12.6%. In addition, in 2018, this cost was recorded at 13.2%. This result was corroborated by Dhoro et al. (2011) and Turgut et al. (2017).

Table 5 also included the findings of the diagnostic analyses where no heteroscedasticity, non-normality, or serial correlation were observed. The results are all within the 0.05 threshold of significance, indicating that the model has remained stable throughout the study time. The Ramsey-RESET statistical test confirms that the model has a valid functional form.

Table 6. Short-run Results of ARDL Model Estimation

Variables	Coefficients	t-statistic	Variables	Coefficients	t-statistic
$\Delta lnHEPC_{t-1}$	1.0831***	9.1061	$\Delta lnBR_{t-1}$	453.1921	1.0034
$\Delta lnHEPC_{t-2}$	0.2980**	2.180	$\Delta lnBR_{t-2}$	-543.9537*	-1.8570
$\Delta lnHEPC_{t-3}$	0.4600***	4.0019	$\Delta lnBR_{t-3}$	216.5562**	2.5902
$\Delta lnRGDPPC$	-1.7860	-1.3540	$\Delta lnINFLA$	0.1131*	1.8578
$\Delta lnRGDPPC_{t-1}$	3.8700***	2.6520	$\Delta lnINFLA_{t-1}$	-0.1964***	-3.3248
$\Delta lnRGDPPC_{t-2}$	0.3117	0.2057	$\Delta lnINFLA_{t-2}$	0.0403	0.7263
$\Delta lnRGDPPC_{t-3}$	2.7557*	2.0807	$\Delta lnINFLA_{t-3}$	-0.0686	-1.1842
$\Delta lnEPFPC$	-0.0914	-0.1364	$\Delta lnMR$	-1.1552	-0.2895
$\Delta lnEPFPC_{t-1}$	-1.4358	-2.0660	$\Delta lnMR_{t-1}$	-7.4368	-1.1255
$\Delta lnEPFPC_{t-2}$	-0.9799*	-1.4648	$\Delta lnMR_{t-2}$	14.6753**	2.5229
$\Delta lnEPFPC_{t-3}$	-1.7516***	-2.9508	$\Delta lnMR_{t-3}$	-11.8253***	-3.5535
$\Delta lnBR$	19.5279	0.1612	ECT_{t-1}	-1.5675***	-10.2228

Cointeq = LNHEALTHPC +6.2857×LNGDPPCUSA - 4.0325×LNEPFPC + 3.7220×LNBIRTHRATE - 0.2642×LNINFLA + 3.9178×LNMR - 74.0331

The asterisks ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

The error correction term coefficient is negative and severely impacted (see Table 6). When the equilibrium is shocked, the error correction term describes how quickly it adjusts. The ECT of 1.57 indicates a conversion speed of 157%, and the shock-to-trend anomalies were rectified in less than a year. Figure 2 illustrates the model's stability based on the CUSUM and CUSUMQ tests.

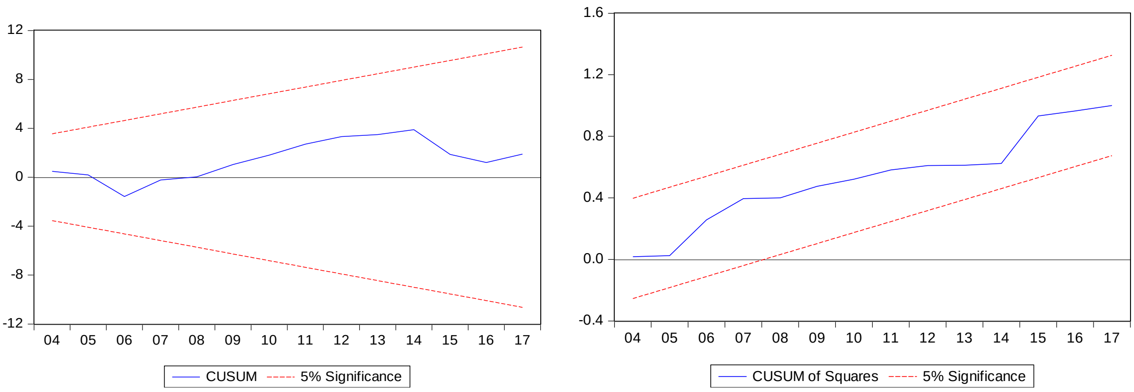

Figure 2 CUSUM and CUSUM SQ Test

4.1 Robustness Analysis

The dynamic OLS, a fully Modified OLS robustness analysis, and Canonical Cointegrating Regression coefficients were employed in this study. The results of the tests confirmed the bulk of the variable signals and matched the ARDL estimates (see Table 7).

Table 7. Fully Modified OLS, Dynamic OLS, and Canonical Cointegrating Regression Coefficients

Variable	**lnHEPC │ lnRGDPPC, lnEPFPC, lnBR, lnINFLA, lnMR**					
	Fully modified OLS		**Dynamic OLS**		**CCR**	
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
LnRGDPPC	-1.8187***	-8.6036	-8.8638***	-4.7548	-1.8788***	-7.3991
lnEPFPC	1.1566***	6.3565	9.7620***	5.1539	0.6653**	2.5979
lnBR	-1.3232***	-8.4036	6.0657**	2.3224	-1.5197***	-7.8965
LnINFLA	0.1568***	6.3649	1.0165***	4.5734	0.17949***	5.2981
LnMR	-2.2840***	-13.2833	-7.0143***	-5.8719	-2.5089***	-12.4059
C	27.232	11.6000	68.7189	2.6898	29.3776	10.5057

The asterisks ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

According to Matthew et al. (2018), this study employed the impulse response function to elucidate how each variable interacts with another variable. The shock towards the independent variable is shown by plotting the impulsive response of a dependent variable. Figure 3 depicts the results of the impulse response function, which spans over thirty years.

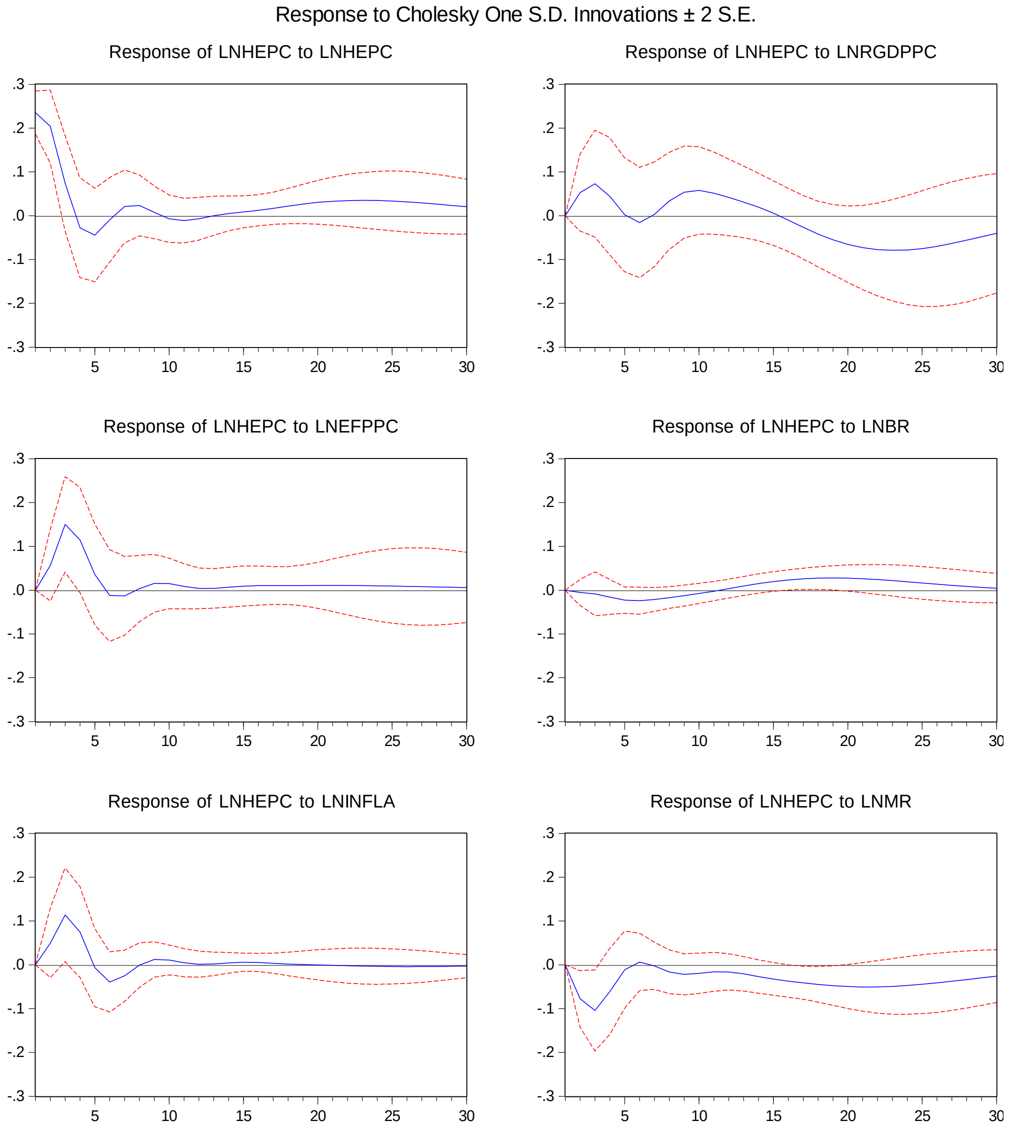

Figure 3. Impulse Response Function

Based on the results, all variables' bottom and upper boundaries reflect a 95% confidence interval. As illustrated, a positive standard deviation shock was applied to all residuals to investigate how health expenditure responded to this innovation. The impact of health expenditure on GDP was significant where it firstly surged, fell, and then increased. The health expenditure graph then fell until it reached a steady-state value, at which it remained in the negative zone until gradually rising. Both EFP innovation and inflation showed a similar pattern. The birth rate innovations show a tiny reduction at first, then an upsurge before stabilizing. The responses of health expenditure to changes in the death rate fell below the steady-state value, increased, and ultimately reached zero. Nevertheless, the spending progressively decreased and stayed constant. In general, all variables eventually found equilibrium.

This study utilized the variance decomposition technique to compare the impact of each variable on public health spending beyond the sample period and used a 30-year forecasting horizon, similar to the impulse response function (Table 8).

Table 8. Variance Decomposition Analysis

		Impulse Response					
Response variable	**Period**	**LnHECP**	**LnRGDPPC**	**LnEFPPC**	**LnBR**	**LnINFLA**	**LnMR**
LnHEPC	5	53.1332	5.04798	20.2378	0.4443	10.6452	10.4915
	10	50.0087	8.2730	19.2176	1.14234	11.0472	10.3111
	15	47.9342	10.4950	18.4758	1.4148	10.5981	11.0822
	20	43.8876	13.3571	16.7452	2.6633	9.4953	13.8515
	25	38.5143	20.9307	14.1285	3.0180	7.9255	15.4831
	30	36.5102	24.1688	13.0773	2.9086	7.3118	16.0233

The results reveal a 36.5% variance in the release of health expenses on the variable's innovative shock. Alternatively, GDP per capita has the most significant impact (24.16%). The variance was also influenced by EFP (13.08%), inflation (7.31%), and mortality rate (16.02%). Conversely, the birth rate had the most negligible impact on health spending, at only 2.91%. This study corroborates the theory that developing countries such as Malaysia have a significant increase in health spending due to economic development. This circumstance emphasizes the need to attain a certain level of wealth to decrease government health spending. More crucially, the government can then shift the responsibility from subsidizing health to other critical development and public infrastructure expenses.

5. Conclusions and Policy Implication

The ARDL approach was used to verify the association between climatic change, socioeconomic characteristics, and technology and health spending in Malaysia. The empirical results reveal that real GDP per capita, birth rate, and death rate are all adversely significant in the long-term regarding health spending. Conversely, climate change and inflation are both positively significant.

Health spending is essential for societal welfare and stability but should not burden the government. The government should boost investment and highlight healthcare spending as a sign of respect to ensure the wellbeing of citizens. Furthermore, investments in practical innovations and R&D in healthcare technologies are significant for health expenditure. Thus, the government should develop a modern healthcare system, sophisticated medical and healthcare technology, sufficient facilities, equipment, and qualified personnel to ensure socio-economic stability.

Climate change has a substantial influence on human health. Chemicals emitted by environmental waste may increase government expenditures to mitigate the pollution. Consequently, a continual strategy for limiting ecological destruction, such as investing in low-carbon development, creating climate resilience, and prioritizing increased healthcare expenditure, may decrease climate change and safeguard the environment in the future. Coordinated efforts from all stakeholders are urgently required to fulfill sustainable development goals. Technological and organic management advancements that can reduce EFP should motivate policymakers to marshal the power of innovation and implement a new economic model.

Furthermore, the inflation rate should be monitored regularly to improve government health expenditures. Alternatively, governments should apply monetary policies to limit inflation by lowering imports and increasing local products. Macroeconomic stability can boost output and stimulate economic development.

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