

FORECASTING MEDICAL INFLATION IN RELATION TO MEDICAL COST COMPONENTS: A COMPARATIVE APPROACH BETWEEN TRADITIONAL ECONOMETRIC AND MACHINE LEARNING MODELS

(Ramalan Inflasi Perubatan Berkaitan Komponen Kos Perubatan: Pendekatan Perbandingan antara Model Ekonometrik Tradisional dan Pembelajaran Mesin)

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ABSTRACT

Medical inflation has become a critical concern in modern economies due to its profound impact on healthcare affordability and accessibility. This study examines relationship between medical inflation and its underlying cost components, including Medical Care, Medical Care Commodities, Prescription Drugs, Medical Care Services, Professional Services, Physicians' Services, Dental Services, and Hospital Services. This research aims to forecast future medical inflation rates by employing a comparative modelling framework that integrates both traditional econometric models and modern machine learning techniques. This research applies Vector Autoregression (VAR) and Autoregressive Distributed Lag (ARDL) as traditional econometric models, alongside Random Forest (RF) and Artificial Neural Network (ANN), as the representative machine learning models, to evaluate their effectiveness in forecasting. The research involves analysing time series data and identifying the influence of each medical cost component on overall medical inflation. Both short-term and long-term relationships are assessed using econometric models. In contrast, the machine learning model captures complex, non-linear patterns in the data. Forecasting accuracy is compared across models using standard performance metrics to determine the most reliable method for predicting medical inflation from 2025 to 2030. By combining econometric theory with modern data science techniques, this study offers insights into the drivers of medical inflation. It presents a comprehensive evaluation of forecasting methods. The findings contribute to better healthcare planning and cost management by identifying which components most significantly affect inflation, and which modelling approach yields the most accurate forecasts.

Keywords: medical inflation; machine learning; forecasting; econometric

ABSTRAK

Inflasi perubatan telah menjadi kebimbangan kritikal dalam ekonomi moden disebabkan kesannya yang mendalam terhadap kemampuan dan aksesibiliti penjagaan kesihatan. Kajian ini meneroka hubungan kompleks antara inflasi perubatan dan komponen kos asasnya, khususnya Penjagaan Perubatan, Komoditi Penjagaan Perubatan, Ubat Preskripsi, Perkhidmatan Penjagaan Perubatan, Perkhidmatan Profesional, Perkhidmatan Doktor, Perkhidmatan Pergigian, dan Perkhidmatan Hospital. Tujuan kajian ini adalah untuk meramalkan kadar inflasi perubatan masa hadapan dengan menggunakan kerangka pemodelan perbandingan yang menggabungkan model ekonometrik tradisional dan teknik pembelajaran mesin moden. Penyelidikan ini menggunakan Vector Autoregression (VAR) dan Autoregressive Distributed Lag (ARDL) sebagai model ekonometrik tradisional, bersama Random Forest (RF) dan Artificial Neural Network (ANN) sebagai model pembelajaran mesin, untuk menilai keberkesanan setiap kaedah dalam ramalan. Kajian ini melibatkan analisis data siri masa dan mengenal pasti pengaruh setiap komponen kos perubatan terhadap keseluruhan inflasi perubatan. Hubungan jangka pendek dan

jangka panjang dinilai menggunakan model ekonometrik, manakala model pembelajaran mesin mengenal pasti corak kompleks dan tidak linear dalam data. Ketepatan ramalan dibandingkan antara model-model menggunakan metrik prestasi piawai bagi menentukan kaedah yang paling boleh dipercayai untuk meramalkan inflasi perubatan dari tahun 2025 hingga 2030. Dengan menggabungkan teori ekonometrik dan teknik sains data moden, kajian ini menawarkan pandangan mendalam terhadap pemacu inflasi perubatan dan memberikan penilaian menyeluruh terhadap kaedah ramalan. Dapatan kajian ini menyumbang kepada perancangan penjagaan kesihatan dan pengurusan kos yang lebih baik dengan mengenal pasti komponen yang paling mempengaruhi inflasi dan pendekatan pemodelan yang memberikan ramalan paling tepat.

Kata kunci: inflasi perubatan; pembelajaran mesin; ramalan; ekonometrik

1. Introduction

Medical inflation has frequently risen faster than overall consumer inflation, creating growing financial burdens for governments, insurers, and households. In the United States, national health expenditures increased by 7.5% in 2023, reflecting sharp growth in hospital and clinical spending (Reuters 2024). Global projections similarly indicate continued health care cost escalation, with employer-sponsored medical trend rates expected to reach approximately 10.4% in 2025, driven by rising service utilisation, pharmaceutical cost pressures, and rapid adoption of advanced medical technologies (Willis Towers Watson 2024).

The increase in health care costs requires accurate forecasting frameworks for medical inflation to provide inform pricing decisions, resource planning, and policy interventions related to health care. Medical inflation is influenced by multiple structural drivers, including demographic ageing, technological advancement, pharmaceutical pricing, and consolidation within healthcare delivery markets (Erker 2024). Labour cost inflation further intensifies these pressures, as healthcare providers across many countries, including the United States, continue to face persistent workforce shortages and rising wage demands, particularly among nursing and specialised clinical staff (American Hospital Association 2026; Kaufman Hall 2024). Together, these dynamics challenge the effectiveness of traditional linear forecasting models and highlight the need for more adaptable and robust predictive approaches.

Conventional econometric models such as Vector Autoregression (VAR) and Autoregressive Distributed Lag (ARDL) have long been used to analyse and forecast healthcare spending and inflation because of their ability to represent dynamic interactions among cost drivers and assess both short- and long-run relationships. While ARDL remains effective for mixed-integration time series, recent studies emphasise that its reliance on linear long-run equilibrium relationships may overlook the complex, nonlinear dynamics typical of healthcare systems (Mohd Nasir *et al.* 2021). Similarly, although VAR models offer flexibility in modelling multivariate temporal relationships without strict structural assumptions, their performance declines when confronted with high-dimensional datasets, structural breaks, or nonlinear patterns that increasingly characterise modern healthcare expenditure trends (Ye & Zhang 2018). In contrast, emerging evidence demonstrates that machine learning approaches, particularly Random Forests (RF) and Artificial Neural Networks (ANN), significantly outperform traditional econometric techniques in capturing nonlinearities, variable interactions, and temporal heterogeneity in health and economic data (Behrouz & Harrison 2025). These adaptive models can incorporate large, complex datasets and evolving cost structures, leading

to superior predictive accuracy in healthcare cost and inflation forecasting compared with legacy time-series methods.

While medical inflation has been widely studied, existing literature lacks a unified evaluation of how econometric and machine learning models differ in forecasting performance when all major cost components are incorporated. Given the rising volatility in healthcare prices, traditional econometric models may be insufficient for capturing non-linear and evolving cost dynamics. Machine learning approaches, although increasingly popular, have not been systematically compared against VAR and ARDL within the medical inflation context. This gap limits policymakers' ability to choose appropriate forecasting methods. Hence, this study is necessary to address the methodological uncertainty and provide empirical evidence on which modelling framework yields superior predictive accuracy for medical inflation forecasting.

This study makes several important contributions to the existing literature on medical inflation forecasting. It provides a comprehensive comparative evaluation of four distinct modelling approaches, including VAR, ARDL, Random Forest, and Artificial Neural Networks, making it the first study to assess these methods simultaneously using all eight major medical cost components. By integrating multiple cost drivers into a unified forecasting framework, the study moves beyond prior research that typically focuses on individual components such as pharmaceuticals or hospital services. The findings also highlight the advantages of machine learning models, particularly ANN and RF, in capturing nonlinear patterns and outperforming traditional econometric models. Importantly, the study offers practical, policy-relevant insights by identifying forecasting methods that can support insurers, regulators, and healthcare planners in premium pricing, budget allocation, and long-term cost containment.

2. Factors that Affect Medical Inflation

Medical inflation refers to the annual increase in healthcare-related expenditures and reflects a complex interaction of economic, demographic, and structural forces within health systems. Recent international analyses show that medical inflation consistently outpaces general inflation due to rising service utilisation, higher input costs, labor shortages, and expanding adoption of advanced medical technologies (OECD 2023; WHO 2024). Empirical studies from both high-income and middle-income countries demonstrate that hospitalisation, pharmaceutical prices, and specialist services are among the most significant contributors to healthcare expenditure growth, collectively explaining a substantial portion of medical cost escalation (Mohd Nasir *et al.* 2021). These findings align with broader evidence from the United States, where administrative complexity, chronic disease prevalence, ageing populations, and technology-driven care models have been identified as major structural cost drivers (Cox *et al.* 2025; Centers for Medicare & Medicaid Services 2024). Although multiple interacting factors influence medical inflation simultaneously, the components linked to direct patient care, such as hospital services, prescription drugs, and professional fees, remain the most quantifiable and consistently associated with upward pressure on healthcare spending.

2.1. Demographic Changes (Ageing Population)

Population ageing is widely recognised as a major driver of rising healthcare costs, as growing numbers of older adults increase demand for medical services, long-term care, and chronic disease management. Demographic transitions observed across both developed and developing countries have significantly altered patterns of healthcare utilisation, with individuals aged 65

and above consistently consuming more medical resources than younger populations. According to recent analyses from the OECD (2023) and the WHO (2024), older adults require more frequent physician visits, longer hospital stays, expanded pharmaceutical management, and greater reliance on long-term care services, all of which contribute substantially to national healthcare expenditure growth. Cross-country evidence from the European Union (2022) further shows that age-related chronic conditions account for a disproportionately large share of cost increases, particularly in systems facing rapid population ageing. Complementary findings from the Apeagyei *et al.* (2025) reinforce that healthcare spending rises sharply with age due to multimorbidity and increased dependency on specialised and continuous care. Collectively, these trends demonstrate that the expansion of the elderly population imposes persistent and measurable pressures on healthcare budgets worldwide.

The rise of chronic diseases, including cardiovascular disease, diabetes, cancer, and neurodegenerative conditions, has become increasingly intertwined with population ageing, substantially intensifying healthcare demand and contributing to long-term medical cost inflation. As older adults face a higher prevalence of multimorbidity, they require continuous medical supervision, frequent diagnostic assessments, specialist consultations, and long-term pharmacotherapy, all of which escalate healthcare spending over extended periods. Recent global analyses show that chronic disease treatment expenditures grow disproportionately among ageing populations, with healthcare utilisation among individuals aged 65 and above increasing significantly faster than among younger cohorts (WHO 2024; OECD 2023). A multi-country study conducted by the Apeagyei *et al.* (2025) further reports that age-related chronic conditions now account for the largest share of healthcare spending growth in both high-income and middle-income countries, driven by rising disease complexity, longer treatment durations, and increased reliance on specialised medical services. These findings highlight that demographic ageing not only increases baseline healthcare demand but also amplifies the cost intensity of care through persistent management of chronic illnesses.

Technological advancement compounds these pressures, as ageing populations rely heavily on advanced diagnostic, therapeutic, and surgical technologies that carry substantially higher costs than traditional medical interventions. Recent evidence shows that innovations such as robotic-assisted surgery, precision diagnostics, artificial intelligence-enabled monitoring systems, and advanced imaging technologies have significantly improved patient outcomes but have also contributed to a steep rise in per-patient healthcare expenditures, particularly among older adults who are the primary beneficiaries of such technologies (European Union 2022; PwC Health Research Institute 2024; Tang & Dou 2025). Healthcare systems worldwide are experiencing sustained cost growth linked to the integration, maintenance, and continual upgrading of these technologies, as well as the specialised workforce required to operate them. In combination, rapid technological innovation and population ageing form a reinforcing cycle that accelerates medical inflation and places increasing financial strain on healthcare budgets across both developed and developing economies.

2.2. Technological Advancements

Technological innovation has reshaped healthcare delivery worldwide, improving diagnostic accuracy, expanding treatment options, and contributing to better patient outcomes; however, these advances have also accelerated healthcare spending and contributed to medical inflation. The WHO (2024) and the OECD (2023) report that high-cost technologies such as advanced imaging systems, genomic sequencing platforms, robotic-assisted surgical systems, and AI-enabled diagnostic tools—are among the fastest-growing drivers of healthcare expenditure, largely because they require significant financial investment, specialised personnel, and

continuous system upgrades. Recent analyses have shown that technology-related spending accounts for a substantial share of growth in per-capita healthcare costs, particularly in high-income countries where technology adoption is rapid and widespread (OECD 2023; PwC Health Research Institute 2024). Although many of these innovations enhance efficiency and clinical outcomes, their cumulative operational costs including maintenance cycles, consumables, integration with electronic health systems, cybersecurity requirements, and professional training thus creating ongoing fiscal pressures for healthcare providers.

Hospitals increasingly face rising expenditures associated with digital transformation initiatives and emerging clinical technologies. Studies from HIMSS and Deloitte (2023–2024) indicate that implementing artificial intelligence (AI) diagnostic platforms, telemedicine ecosystems, precision-medicine frameworks, and predictive analytics tools requires substantial capital investment beyond the acquisition cost. These technologies demand continuous software licensing, interoperability development, cybersecurity infrastructure, and ongoing staff upskilling to maintain safe and effective operation (Deloitte 2024; HIMSS 2025). Furthermore, advanced technologies often generate additional clinical procedures such as follow-up testing triggered by highly sensitive imaging or screening tools—which may inadvertently increase utilisation and, ultimately, total spending. Recent economic evaluations also highlight that while minimally invasive and robotic-assisted surgeries can shorten recovery times, they frequently raise procedural costs due to expensive devices, instrument replacement cycles, and the specialised workforce required (European Union 2022; Tang & Dou 2025).

As a result, technological innovation exerts a dual influence on healthcare systems: it simultaneously improves the quality of care while driving sustained long-term spending growth. Evidence from OECD (2023) and WHO (2024) emphasises that technology-induced cost escalation remains one of the most complex sources of upward pressure on medical prices globally. This paradox of higher quality accompanied by higher costs illustrates why technological advancement is considered a major structural contributor to medical inflation in both developed and emerging healthcare markets.

2.3. Gross Domestic Product (GDP) per Capita Growth

Economic development, commonly measured through growth in GDP and income per capita, remains one of the most consistent predictors of national healthcare spending. As countries experience rising incomes, demand for healthcare services typically increases, driven by greater expectations for quality care, expanded insurance coverage, and higher utilisation of medical services. Recent international data show that wealthier economies allocate a larger share of their resources to health and exhibit higher per capita health expenditure, confirming a long-run positive association between economic capacity and healthcare spending (OECD 2023; 2025). Malaysia shows a similar pattern: although its health expenditure as a percentage of GDP remains below OECD averages, national spending increased to 5.1% of GDP in 2021 before moderating in subsequent years, reflecting the influence of evolving fiscal capacity and healthcare demand as the economy grows (World Bank 2025). These observations reinforce the view that economic expansion strengthens a nation's ability to finance healthcare and meet rising population health needs.

Recent cross-country analyses, however, highlight that the relationship between income growth and healthcare spending is not strictly proportional. Beyond certain income thresholds, health spending often increases at a slower rate relative to GDP, suggesting diminishing marginal effects as systems mature and reach higher efficiency or saturation levels (OECD 2025). This nuanced relationship indicates that while economic growth initially drives substantial increases in healthcare utilisation, particularly through expanded access,

technological adoption, and treatment intensity, continued spending growth depends on how effectively health systems convert financial resources into productivity and performance improvements. Without gains in efficiency, escalating expenditures can place pressure on government budgets and weaken the long-term alignment between economic development and health system sustainability.

2.4. Medical Cost Component

The medical cost components are significant sources of healthcare inflation due to rising prices in various elements of healthcare. Such impacts should be understood to comprehend why healthcare remains unaffordable despite ongoing improvements and technological advances within the field.

2.4.1. Physician services

Physician services are an important driver of healthcare cost growth because higher utilisation of physician-delivered care, whether through more frequent visits, additional diagnostic orders, or defensive medicine, raises system spending. Evidence shows clinicians often lack full awareness of service costs, which contributes to overordering of tests and procedures and to avoidable expenditure (Fabes *et al.* 2022). Payment systems based on fee-for-service (FFS) create financial incentives to increase volumes of billable services, and empirical reviews show that shifting away from pure FFS toward prospective or value-based payment can reduce unnecessary utilisation and moderate cost growth. Meanwhile, consolidation of physician practices into larger health systems or hospital ownership has been associated with higher prices for outpatient and professional services, as larger consolidated entities acquire greater market power (Congressional Budget Office 2024). Taken together, clinician behaviour, payment design, and market structure combine to make physician services a persistent contributor to medical inflation.

2.4.2. Dental care

Dental care costs exert upward pressure on overall household medical spending in settings where dental coverage is limited, and many services are paid out-of-pocket. Recent policy and empirical work documents that gaps in public dental coverage force many patients to seek private care at higher prices, and that expansion of public dental benefits tends to increase access but requires careful design to control costs and provider participation (Scannapieco & Lamster 2024). Digital dentistry and newer clinical technologies (CAD/CAM systems, intraoral scanners, 3D printing) have improved diagnostic precision and treatment quality but also raise clinic capital and operating costs, which can be passed to patients in the private market (Pasupuleti *et al.* 2024). These structural factors, such as limited insurance coverage, adoption of higher-cost technologies, and price opacity, help explain why dental services contribute meaningfully to medical-cost burdens in many countries.

2.4.3. Hospital services

Hospital services are among the largest components of health spending and therefore a central driver of medical inflation. In many countries, rising inpatient and outpatient hospital expenditures which are driven by higher prices for hospital care, increased use of specialist services, and growth in intensive and technologically intensive care. These have accounted for a large share of recent increases in total health spending (Beasley 2024). Hospital provision costs also absorb substantial shares of equipment, drug, and staffing budgets, leading hospitals

to pass rising input costs on to payers. Country-specific reviews note that in Malaysia and similar markets, hospital charges, pharmaceuticals, and diagnostic services are major contributors to private medical cost inflation.

2.4.4. Prescription drugs

Prescription drug prices have been a major upward pressure on medical spending, particularly for new specialty therapies launched at very high list prices. Recent reporting and analyses show steep year-on-year increases in launch prices for novel drugs and rapid growth in spending on oncology and rare-disease therapies, which have materially increased payer and patient out-of-pocket costs (Beasley 2024). Policy mechanisms in some jurisdictions (e.g., the U.S. Inflation Reduction Act) have started to constrain price trajectories for certain Medicare drugs, but overall drug launch and list-price trends remain a significant driver of medical inflation in many health systems.

2.4.5. Professional and medical services

Professional and allied-medical services, including specialist consultations, diagnostics, and reimbursable procedures, contribute to inflation when input costs and overhead rise faster than reimbursement updates. In some countries, clinicians and small private practices face rapid increases in operational costs (rent, utilities, staff wages and supplies), prompting fee increases or clinic consolidation; this dynamic has been documented in recent Malaysian industry analyses and market reports that note rising provider cost pressures and fee adjustment demands (MIDF Research Team 2025). Where primary care or outpatient clinics close or consolidate, patients may shift to higher-cost hospital outpatient services, further increasing system spending.

2.4.6. Medical care services

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2.4.7. Medical commodities

Rising prices for medical commodities, including pharmaceuticals, diagnostic reagents, medical devices, and consumables, have amplified overall health spending. Global supply-chain disruptions, input-price inflation, and currency volatility for import-dependent markets have increased procurement costs for hospitals and clinics, which are frequently passed on in the form of higher charges for services and products. This is particularly pronounced in countries that rely heavily on imported equipment and pharmaceuticals; analyses of supply-chain pressures and commodity price trends underscore their role in recent medical-cost increases.

3. Data and Methodology

In this section, the methodology adopted for this project will be discussed. This section will cover the selection process of data acquisition, the development of predictive models using traditional time series models, including VAR and ARDL, as well as machine learning models, such as RF and ANN. The models will then be evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination, also known as R-squared (R^2).

3.1. Data Acquisition

The dataset on each variable is obtained from different sources. Medical inflation data were obtained from the US Inflation Calculator's Health Care Inflation (HCI) page, and the medical components data were retrieved from the US Bureau of Labor Statistics (BLS). All variables were collected at monthly frequency, covering the sample period from January 1977 to December 2024, depending on data availability for each component. The data is sorted into nine variables: medical inflation, medical care, medical commodities, prescription drugs, medical care services, professional services, physicians' services and dental services. Note that these data were collected by exporting the data and extracting it into Excel.

Table 1: Data description

Indicators	Abbreviation	Sources
Medical Inflation	MI	US Inflation Calculator : Health Care Inflation (1948-2024)
Medical Care	MC	BLS : Medical Care (1935-2024)
Medical Care Commodities	MCC	BLS : Medical Care Commodities (1987-2024)
Prescription Drugs	PD	BLS : Prescription Drugs (1935-2024)
Medical Care Services	MCS	BLS : Medical Care Services (1977-2024)
Professional Services	PRS	BLS : Professional Services (1977-2024)
Physicians' Services	PHS	BLS : Physicians' Service (1935-2024)
Dental Services	DS	BLS : Dental Services (1935-2024)
Hospital Services	HS	BLS : Hospital Services (1977-2024)

To evaluate model performance and ensure generalisability, the dataset was partitioned into a training set (70%) and a testing set (30%), a widely accepted proportion in machine-learning and forecasting research. A 70:30 split provides sufficient data for model learning while preserving an adequate holdout sample for unbiased performance assessment, particularly in healthcare forecasting applications where overfitting is a key concern. Recent methodological studies emphasise that allocating approximately two-thirds of the data for training and the remaining portion for testing supports stable parameter estimation while enabling reliable evaluation of predictive accuracy on unseen observations (Teja & Rayalu 2025). Similarly, applied health-prediction research demonstrates that a 70:30 division balances variance and bias effectively in neural networks and ensemble models, especially when working with complex, nonlinear relationships found in healthcare expenditure and outcome datasets (Kumagai & Jakovljević 2024). This approach is consistent with standard machine-learning validation practices, which recommend using a dedicated test set to measure true out-of-sample performance after model optimisation and hyperparameter tuning (Ricci *et al.* 2025).

3.2. Vector Auto Regression

The Vector Autoregression (VAR) model extends traditional autoregressive time-series approaches by treating all variables as endogenous, allowing researchers to capture the complex and dynamic interactions among economic and healthcare indicators. This makes VAR particularly suitable for analysing healthcare systems, where expenditures, demographic pressures, and service utilisation evolve interdependently over time. Recent empirical studies demonstrate that VAR and its extensions remain valuable tools in health economics. For example, panel VAR methods have been used to investigate how medical and long-term care expenditures influence one another in ageing health systems, revealing significant bidirectional relationships and adjustment dynamics (Sugawara *et al.* 2024). Similarly, VAR-based analyses of long-term care spending in European contexts highlight how policy, demographic change, and expenditure patterns jointly drive healthcare cost trajectories (Costa-Font & Vilaplana-Prieto 2023). In comparative forecasting research, VAR models continue to perform competitively against nonlinear machine-learning techniques when examining the macroeconomic determinants of healthcare expenditure across emerging markets (Ye & Zhang 2018). These findings reinforce that VAR remains a robust and versatile framework for modeling and forecasting the interconnected economic forces that shape healthcare expenditure.

The eight equations listed for VAR models have eight independent variables as per Eq. 1 to Eq. 9 below.

$$\begin{aligned}
 MI_t = & \beta_0 + \beta_1 MC_t + \beta_2 MCC_t + \beta_3 PD_t + \\
 & \beta_4 MCS_t + \beta_5 PRS_t + \beta_6 PHS_t + \\
 & \beta_7 DS_t + \beta_8 HS_t + \varepsilon_t.
 \end{aligned} \tag{1}$$

$$\begin{aligned}
 MC_t = & C_1 + \beta_{11} MC_{t-1} + \beta_{12} MCC_{t-1} + \\
 & \beta_{13} PD_{t-1} + \beta_{14} MCS_{t-1} + \beta_{15} PRS_{t-1} + \\
 & \beta_{16} PHS_{t-1} + \beta_{17} DS_{t-1} + \beta_{18} HS_{t-1} + \varepsilon_{1,t}.
 \end{aligned} \tag{2}$$

$$\begin{aligned}
 MCC_t = & C_2 + \beta_{21} MC_{t-1} + \beta_{22} MCC_{t-1} + \\
 & \beta_{23} PD_{t-1} + \beta_{24} MCS_{t-1} + \\
 & \beta_{25} PRS_{t-1} + \beta_{26} PHS_{t-1} + \\
 & \beta_{27} DS_{t-1} + \beta_{28} HS_{t-1} + \varepsilon_{2,t}.
 \end{aligned} \tag{3}$$

$$\begin{aligned}
 PD_t = & C_3 + \beta_{31} MC_{t-1} + \beta_{32} MCC_{t-1} + \\
 & \beta_{33} PD_{t-1} + \beta_{34} MCS_{t-1} + \\
 & \beta_{35} PRS_{t-1} + \beta_{36} PHS_{t-1} + \\
 & \beta_{37} DS_{t-1} + \beta_{38} HS_{t-1} + \varepsilon_{3,t}.
 \end{aligned} \tag{4}$$

$$\begin{aligned}
 MCS_t = & C_4 + \beta_{41} MC_{t-1} + \beta_{42} MCC_{t-1} + \\
 & \beta_{43} PD_{t-1} + \beta_{44} MCS_{t-1} + \\
 & \beta_{45} PRS_{t-1} + \beta_{46} PHS_{t-1} + \\
 & \beta_{47} DS_{t-1} + \beta_{48} HS_{t-1} + \varepsilon_{4,t}.
 \end{aligned} \tag{5}$$

$$\begin{aligned}
 PRS_t = & C_5 + \beta_{51}MC_{t-1} + \beta_{52}MCC_{t-1} + \\
 & \beta_{53}PD_{t-1} + \beta_{54}MCS_{t-1} + \\
 & \beta_{55}PRS_{t-1} + \beta_{56}PHS_{t-1} + \\
 & \beta_{57}DS_{t-1} + \beta_{58}HS_{t-1} + \varepsilon_{5,t}.
 \end{aligned} \tag{6}$$

$$\begin{aligned}
 PS_t = & C_6 + \beta_{61}MC_{t-1} + \beta_{62}MCC_{t-1} + \\
 & \beta_{63}PD_{t-1} + \beta_{64}MCS_{t-1} + \\
 & \beta_{65}PRS_{t-1} + \beta_{66}PHS_{t-1} + \\
 & \beta_{67}DS_{t-1} + \beta_{68}HS_{t-1} + \varepsilon_{6,t}.
 \end{aligned} \tag{7}$$

$$\begin{aligned}
 DS_t = & C_7 + \beta_{71}MC_{t-1} + \beta_{72}MCC_{t-1} + \\
 & \beta_{73}PD_{t-1} + \beta_{74}MCS_{t-1} + \\
 & \beta_{75}PRS_{t-1} + \beta_{76}PHS_{t-1} + \\
 & \beta_{77}DS_{t-1} + \beta_{78}HS_{t-1} + \varepsilon_{7,t}.
 \end{aligned} \tag{8}$$

$$\begin{aligned}
 HS_t = & C_8 + \beta_{81}MC_{t-1} + \beta_{82}MCC_{t-1} + \\
 & \beta_{83}PD_{t-1} + \beta_{84}MCS_{t-1} + \\
 & \beta_{85}PRS_{t-1} + \beta_{86}PHS_{t-1} + \\
 & \beta_{87}DS_{t-1} + \beta_{88}HS_{t-1} + \varepsilon_{8,t}.
 \end{aligned} \tag{9}$$

3.3. Autoregressive Distributed Lag

ARDL model is widely recognised as a flexible approach for assessing both short-run adjustments and long-run equilibrium relationships in time-series data, particularly when variables are integrated of mixed orders. This makes ARDL well suited for analysing medical inflation and healthcare expenditures, which often evolve unevenly in response to macroeconomic shocks and policy changes. Recent empirical studies examining the determinants of healthcare spending in low- and middle-income countries have applied ARDL-type frameworks to capture delayed and asymmetric responses of health expenditure to movements in income, demographic pressures, and service-delivery costs (Mohd Nasir *et al.* 2021). Similar research using time-series and panel-time-series econometric models consistent with ARDL logic has demonstrated how healthcare expenditure adjusts gradually to economic growth and structural changes, reinforcing the model's value for policy analysis in emerging economies (Wang & Chen 2022). These findings confirm that ARDL remains a robust methodological tool for evaluating dynamic health-expenditure relationships and informing health-financing strategies. The variables may be stationary, nonstationary, or both. The simple expression of the ARDL was exhibited as shown in Eq. 10 below.

$$\begin{aligned}
 MI_t = & \beta_0 + \beta_1MC_t + \beta_2MCC_t + \beta_3PD_t + \\
 & \beta_4MCS_t + \beta_5PRS_t + \beta_6PHS_t + \\
 & \beta_7DS_t + \beta_8HS_t + \varepsilon_t.
 \end{aligned} \tag{10}$$

To provide more consistency and efficiency in the outcomes, all variables in this study were transformed into Natural Logarithms (LN). The log-linear model, denoted as LN, can be described as Eq. 11 below.

$$\begin{aligned} LNMI_t = & \beta_0 + \beta_1 LNM C_t + \beta_2 LNM C C_t + \\ & \beta_3 LNP D_t + \beta_4 LNM C S_t + \beta_5 LNPR S_t + \\ & \beta_6 LNPH S_t + \beta_7 LND S_t + \beta_8 LNHS_t + \varepsilon_t. \end{aligned} \quad (11)$$

Finally, the model was converted into an Unrestricted Error Correction Model (UECM) equation as per Eq. 12.

$$\begin{aligned} \Delta LNMI_t = & \beta_0 + \beta_1 LNM C_t + \beta_2 LNM C C_{t-i} + \\ & \beta_3 LNP D_{t-i} + \beta_4 LNM C S_{t-i} + \beta_5 LNPR S_{t-i} + \\ & \beta_6 LNPH S_{t-i} + \beta_7 LND S_{t-i} + \beta_8 LNHS_{t-i} + \varepsilon_t + \\ & \sum_{i=1}^{k_1} \delta_1 LNM C_{t-i} + \sum_{i=1}^{k_2} \delta_2 LNM C C_{t-i} + \\ & \sum_{i=1}^{k_3} \delta_3 LNP D_{t-i} + \sum_{i=1}^{k_4} \delta_4 LNM C S_{t-i} + \\ & \sum_{i=1}^{k_5} \delta_5 LNPR S_{t-i} + \sum_{i=1}^{k_6} \delta_6 LNPH S_{t-i} + \\ & \sum_{i=1}^{k_7} \delta_7 LND S_{t-i} + \sum_{i=1}^{k_8} \delta_8 LNHS_{t-i}. \end{aligned} \quad (12)$$

3.4. Random Forest

RF is a flexible ensemble learning method that constructs a large number of individual decision trees and aggregates their outputs to improve predictive performance and reduce overfitting. Its structure naturally accommodates high-dimensional datasets and captures complex, nonlinear interactions between predictors that are common in healthcare data, such as demographic, clinical, and utilisation variables. Recent healthcare research has successfully applied RF models to forecast medical out-of-pocket costs for patients with chronic conditions, demonstrating that RF can accurately model nonlinear relationships among health determinants and cost outcomes while highlighting key predictors such as age, comorbidities, and lifestyle factors (Kumagai & Jakovljević 2024). One of the key advantages of RF is its ability to rank variable importance, which aids policymakers and healthcare planners in identifying the most influential cost drivers and targeting interventions effectively. This robustness to noise and outliers enhances the reliability of RF forecasts relative to some traditional statistical models, particularly when relationships among variables are complex and not well captured by linear specifications. Although direct comparisons with traditional forecasting models like ARIMA in medical inflation contexts are still emerging, evidence from related time-series and machine learning research suggests that RF and hybrid models often provide competitive or superior predictive accuracy when modelling nonlinear trends in health and economic data (Teja & Rayalu 2025).

RF healthcare inflation forecasting technique comprises several steps. The first step involves preparing data where healthcare inflation is considered the dependent variable, medical cost components are the explanatory variables, and the data is preprocessed to eliminate missing values and generate lag features. The data would be divided into a training and a test set.

Hyperparameters, such as tree depth (for which the maximum limit was not set) and the number of trees (set to 100), are optimised to perform best. The predictions of several trees may be used to form the aggregation that transforms the model. Correspondingly, this is applied in predicting future inflation. The following illustrates a simple example of how RF works, as described by Laudato *et al.* (2020).

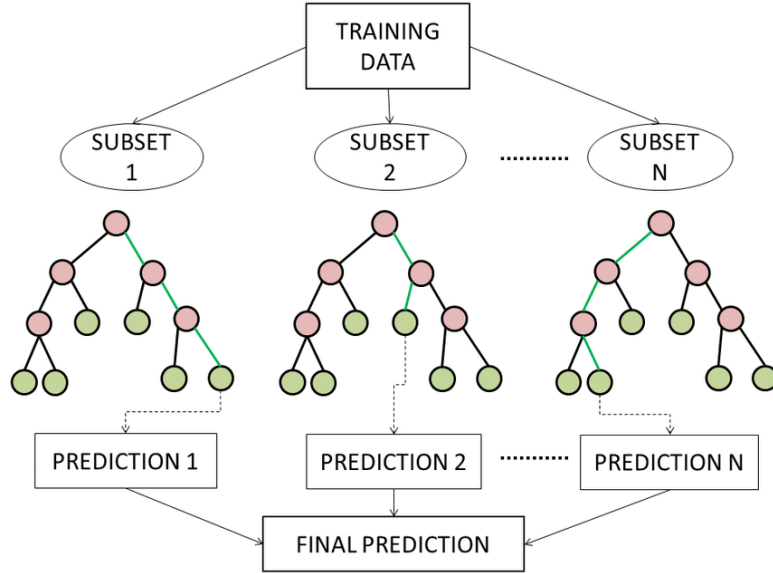


Figure 1: Illustration of RF as per Laudato *et al.* (2020)

Also, the hyperparameters were optimised using Grid Search with 5-fold cross validation chosen to balance computational efficiency and robustness where the parameters were selected based on minimising validation error.

Table 2: Hyperparameter summary for RF

Tuned Parameters	Selected Value	Rationale
n_estimators	100	Balances bias-variance, avoids overfitting
max_depth	None	Allows full tree growth for complex patterns
min_samples_split	2	Standard for high-complexity data
max_features	sqrt	Best for time-series predictors

3.5. Artificial Neural Network (ANN)

ANNs are powerful nonlinear modelling tools inspired by the structure of the human brain, consisting of interconnected layers of artificial neurons that can learn complex patterns from data without requiring extensive manual feature engineering. ANNs are especially effective at capturing intricate nonlinear relationships in high-dimensional healthcare datasets, such as those involving demographic, clinical, and cost factors, because they can approximate arbitrary functional forms through nonlinear activation functions and layered architectures. For example, neural network models have been successfully applied to forecast total health expenditure over multi-decadal periods, demonstrating their ability to learn nonlinear interactions between

economic and healthcare determinants that traditional linear models often miss (Saleh *et al.* 2023).

ANNs are typically trained using backpropagation with adaptive optimisation algorithms such as Adam, which adjust learning rates and minimise prediction errors efficiently across epochs, enabling models to adapt to evolving trends in complex data environments. Architectures with multiple hidden layers and activation functions like ReLU help address issues such as vanishing gradients and improve model convergence, while robust preprocessing (e.g., normalisation, handling of missing values) and appropriate training–testing splits ensure reliable evaluation of forecasting accuracy. Because ANNs can quantify learned relationships and identify influential features driving predictions, they offer valuable interpretive and decision-support utility for policymakers seeking to understand the primary drivers of medical cost dynamics and inflation. The following illustrates a simple example of how an ANN works, as described by Kaushik *et al.* (2020).

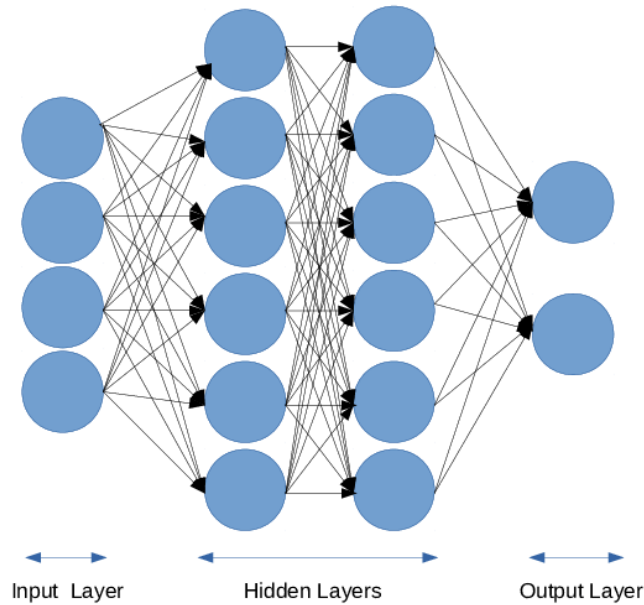


Figure 2: Illustration of ANN as per Kaushik *et al.* (2020)

Also, the hyperparameters were optimised using Grid Search with 5-fold cross validation chosen to balance computational efficiency and robustness where the parameters were selected based on minimising validation error.

Table 3: Hyperparameter summary for ANN

Tuned Parameters	Selected Value	Rationale
Hidden layers	(100, 50)	Captures nonlinear patterns
Activation	ReLU	Prevents vanishing gradients
Learning rate	0.001	Stability during training
Batch size	32	Good for medium datasets
Epochs	300	Ensures convergence

3.6. Evaluation Metrics

Three evaluation metrics, namely MSE, RMSE, and the R^2 value, will be used to assess the performance of the models. MSE measures the average of the squares of the errors, which calculates the average squared differences between the predicted values and the actual values and RMSE taking root of the values. Meanwhile, the R^2 value is a statistical measure that represents the proportion of variance for a dependent variable that is explained by independent variables in a regression model.

To carry out the model evaluation process on the prediction models, ScikitLearn in Python will be used to calculate these values. The following Eq. 13, Eq. 14, and Eq. 15 are the formulas for each metric.

$$MSE = \frac{1}{n} \sum_{i=1}^n (\text{actual output}_i - \text{predicted output}_i)^2 \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\text{actual output}_i - \text{predicted output}_i)^2} \quad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (\text{actual output}_i - \text{predicted output}_i)^2}{\sum_{i=1}^n (\text{actual output}_i - \text{average output}_i)^2} \quad (15)$$

4. Results

The four model strategies, VAR, ARDL, RF, and ANN, were compared in terms of predictive accuracy in predicting HCI using various factors of medical expenditures as input. The results are summarised regarding model evaluation, estimation, comparison, and forecasting.

4.1. Preliminary Analysis

The analysis for this research was started by analysing the patterns of data through descriptive statistics and correlation testing. The results show the state and patterns of the data before proceeding to the actual analysis.

Table 4: Descriptive statistics

Factor	Count	Mean	Std	Variance	Min	25%	Median	75%	Max	Mode
MI	456.00	4.13	1.94	3.77	-1.40	2.90	3.90	4.70	9.70	3.50
MC	456.00	338.14	129.26	16,708.38	126.60	228.48	328.95	446.69	569.19	340.10
MCC	456.00	279.57	81.91	6,709.27	127.60	207.52	280.15	366.33	403.45	207.90
PD	456.00	358.14	128.25	16,448.55	135.80	243.20	356.65	479.78	563.04	214.50
MCS	456.00	353.98	147.89	21,871.44	123.60	225.55	343.80	480.18	618.06	224.30
PRS	456.00	298.73	104.92	11,008.61	121.00	203.62	300.65	392.26	475.28	153.90
PHS	456.00	287.26	86.33	7,452.70	126.60	216.75	289.40	366.41	423.86	217.00
DS	456.00	338.11	135.39	18,329.46	123.90	216.48	330.65	452.74	607.83	311.90
HS	456.00	518.70	284.97	81,209.85	127.90	269.88	451.65	759.43	1,100.10	167.90

The table above presents descriptive statistics for medical inflation and its major cost components based on 456 observations. Overall, MI exhibits a mean of 4.13% with moderate variability (standard deviation = 1.94), indicating persistent but fluctuating price growth over the sample period. Among expenditure components, HS record the highest average level (mean = 518.70) and the greatest dispersion (standard deviation = 284.97), highlighting their dominant and volatile contribution to healthcare costs. Notable variability is also observed in PD and MCS, reflecting sensitivity to pricing dynamics and utilisation changes. In contrast, PHS and PRS display comparatively lower dispersion, suggesting more stable pricing behaviour. The wide ranges between minimum and maximum values across categories indicate substantial heterogeneity in cost movements, underscoring the importance of modelling medical inflation using methods capable of capturing both scale differences and variability across components.

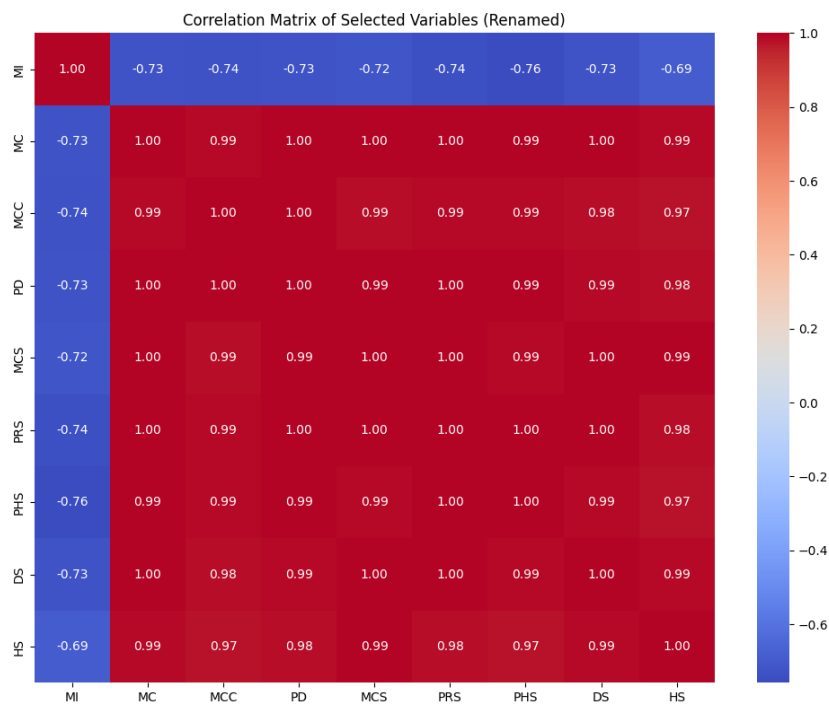


Figure 3: Correlation matrix

Then, the following figure presents the Spearman's correlation matrix between MI and its major cost components. MI exhibits moderate to strong negative correlations with all expenditure categories, with coefficients ranging from -0.69 (HS) to -0.76 (PHS), indicating that increases in component price levels are associated with slower growth in the overall inflation rate over the sample period. In contrast, the individual medical cost components display extremely high positive correlations with one another (generally above 0.97), reflecting strong co-movement and shared underlying cost drivers across healthcare services. This high degree of multicollinearity underscores the interconnected nature of healthcare cost structures and highlights the importance of employing modelling approaches capable of handling highly correlated predictors when forecasting medical inflation.

4.2. VAR Model Performance

Seven predictors were significant from the Multiple Linear Regression (MLR) analysis and were incorporated into the VAR model. The series became stationary ($p < 0.05$, ADF test) after first differencing was carried out. The Characteristic Root Modulus Test was used to verify that the model was stable by removing MC, MCS, HS, and PMIS, ensuring the unit circle condition was met.

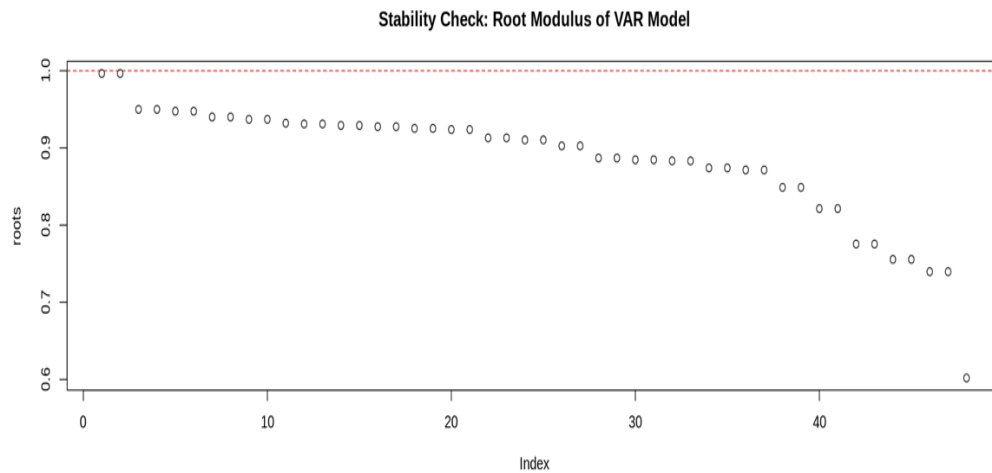


Figure 4: Root modulus test for VAR stability

The result of the Characteristic Root Modulus Test is shown in the following diagram to assess the stability of the VAR model. This indicates that the system should provide quite reliable and consistent forecasts without any explosive behaviour, and that the drop in variables that were unstable before has effectively led to a stable VAR model.

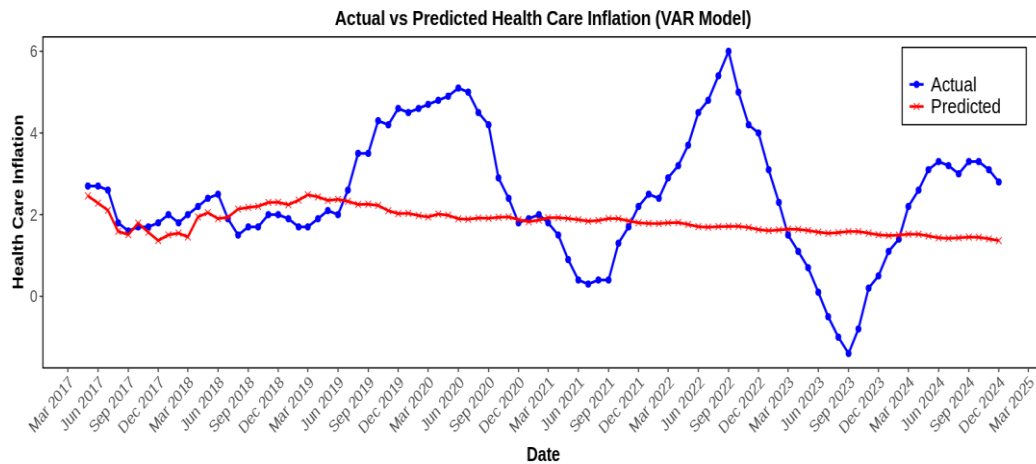


Figure 5: Actual vs predicted health care inflation using VAR

The following graph plots the actual and predicted values of HCI between 2017 and 2024, using the fitted VAR model as per PD, PS, and MCC. This indicates that the VAR model can track the average trend in HCI. However, it does not demonstrate the system's responsiveness to seismic events. It cannot accurately track the volatility in the actual data. The wide volatility in the forecast versus actual trends highlights the model's weakness in capturing even the most complex or non-linear trends, particularly in healthcare inflation.

Therefore, the VAR model had low prediction accuracy. Note that the predictions of the period between 2017 and 2024 did not predict the peaks and troughs in HCI. It was determined to be underperforming according to error metrics, with $MSE = 2.6433$, $RMSE = 1.6258$, and a negative $R^2 = -0.1523$, indicating that the model performed worse than a simple mean-based forecast.

4.3. ARDL Model Performance

The ARDL (2,2,1,1) setup was chosen based on the Akaike Information Criterion (AIC) optimisation, with MC, HS, and PS as shown in Table 5 below. The short-term relationships appeared to be quite strong (all coefficients were highly significant at $p < 0.05$). In long-run coefficients, MC showed a negative influence on HCI (-0.0794), HS and PS were positive (0.0263 and 0.0174, respectively).

Table 5: Coefficient Table for ARDL (2,2,1,1)

Variable	Coefficient	Std. Error	t-value	p-value	Variable
(Intercept)	0.3764	0.1106	3.40	< 0.001 ***	(Intercept)
$L(y, 1)$	1.1989	0.0450	26.64	< 0.001 ***	$L(y, 1)$
$L(y, 2)$	-0.2404	0.0439	-5.47	< 0.001 ***	$L(y, 2)$
$\ln_x1$	0.2450	0.0172	14.27	< 0.001 ***	$\ln_x1$
$L(x1, 1)$	-0.2884	0.0234	-12.33	< 0.001 ***	$L(x1, 1)$
$L(x1, 2)$	0.0401	0.0131	3.06	0.002 **	$L(x1, 2)$
$\ln_x2$	-0.0258	0.0050	-5.16	< 0.001 ***	$\ln_x2$
$L(x2, 1)$	0.0269	0.0050	5.35	< 0.001 ***	$L(x2, 1)$
$\ln_x3$	-0.0275	0.0107	-2.57	0.010 *	$\ln_x3$
$L(x, 1)$	0.0282	0.0106	2.65	0.008 **	$L(x, 1)$

Diagnostic tests indicated that the autocorrelation was acceptable (Breusch-Godfrey $p = 0.65$). Nonetheless, heteroskedasticity and non-normality of residuals were significant. There was no problem of parameter estimation given robust standard errors. Out-of-sample predictions revealed that the ARDL model performed well, with general trends in HCI, but was inaccurate during periods of sudden changes. Evaluation metrics were $MSE = 1.8155$, $RMSE = 1.3474$, and $R^2 = 0.2253$, indicating moderate explanatory power with only low forecast accuracy.

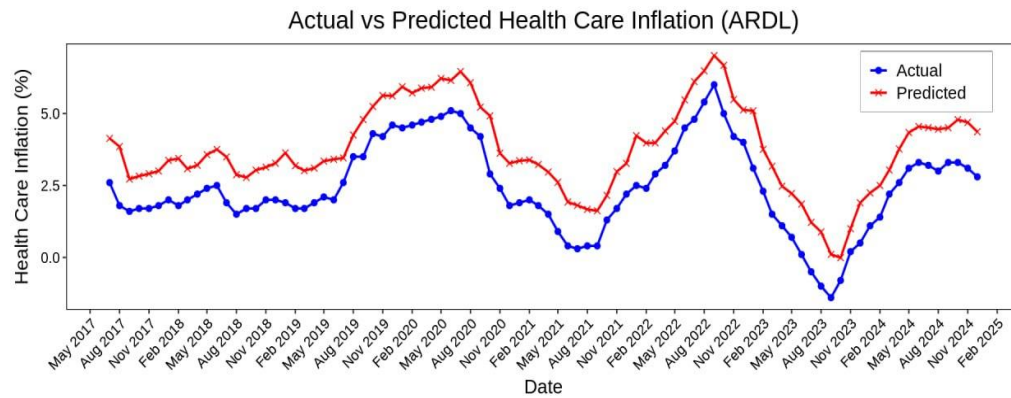


Figure 6: Actual vs predicted HCI using ARDL

The graph provides a visual comparison between the actual and estimated values of HCI during the testing period. As we can see, it captures both long-term trends and shifts, as well as turning points, although it is not as sensitive to points of sudden change, particularly during economic fluctuations.

4.4. Random Forest (RF)

The RF model used lag features of up to 12 months to model time dynamics. Although the model worked well when tracking prominent directional trends in inflation, the build-up in 2019 and the peak in 2022 did not result in significant drops in 2021 or 2023.

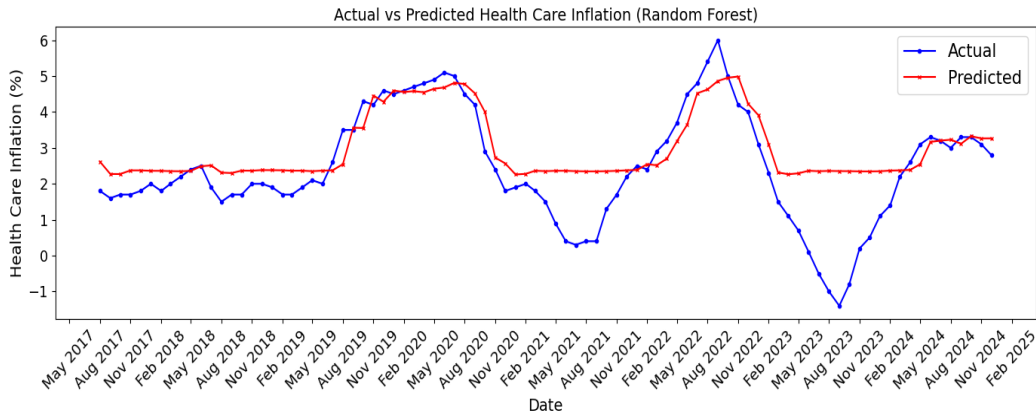


Figure 7: Actual vs predicted health care inflation using random forest

The following graph shows the Actual and Estimated Values of HCI during the testing period, which is illustrated below. It provides a visual comparator that indicates the ability to capture long-term trends and changes, as well as turning points. However, it does not respond as well to sudden changes, particularly during times of economic volatility.

4.5. Artificial Neural Network (ANN)

Most of the models obtained worse results compared to the ANN model created with an MLP regressor having two layers of neurons (100, 50). It reflected seasonality, as well as inflation peaks (e.g., in 2020 and 2022) and lows (e.g., in 2023). Although it minimally underpredicted extreme high and low data points, the model remained consistent over the testing period.

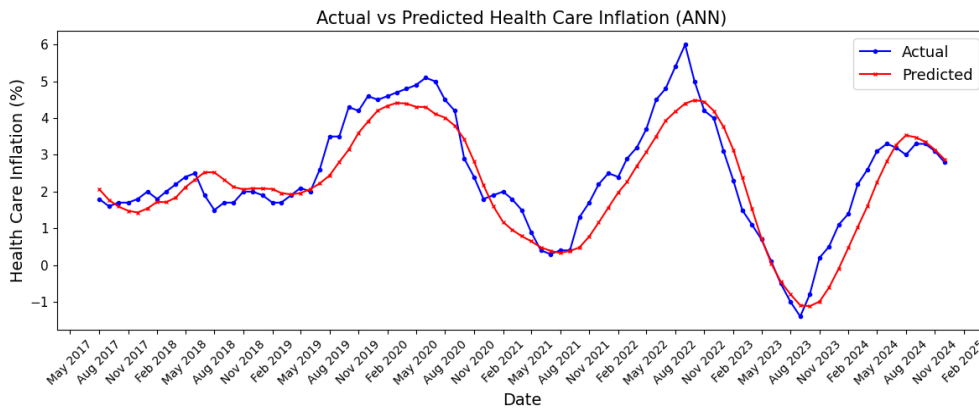


Figure 8: Actual vs predicted HCI using ANN

Figure 8 provides a relative comparison of the actual and estimated values of HCI during the testing period from August 2017 to December 2024. Although the ANN model fails to capture the extreme fluctuating points, it still accurately represents the trend and seasonal fluctuations of HCI very well.

4.6. Model Evaluation

Table 6: Error measures for all models

Model	MSE	RMSE	R ²
ANN	0.3833	0.6191	0.8382
RF	1.1340	1.0649	0.5214
ARDL	1.81552	1.34741	0.22532
VAR	2.6433	1.6258	-0.1523

Generally, the ANN model had the strongest predictive result among all the models, as shown in Table 4, followed by RF, ARDL, and lastly VAR. ANN provided the least prediction error and the best variance explanation, making it appropriate for working with complex, non-linear, and seasonal data. RF demonstrated good predictive capacity, although it was not as accurate as ANN. Although the ARDL is a statistically valid model, it has a limiting aspect due to its linear nature and sensitivity to lag. VAR explained the least and missed the volatility and trends of HCI.

The ANN model delivered the highest forecasting accuracy ($R^2 = 0.8382$), outperforming RF, ARDL, and VAR. This is theoretically consistent with machine learning literature, as ANN captures complex nonlinear interactions among multiple cost components that linear models cannot represent. Medical inflation behaves dynamically and is influenced by interacting factors, such as pharmaceutical pricing, hospital wages, and ageing demographics, whose effects vary over time. The flexibility of ANN in modelling nonlinear response surfaces explains its superior performance.

The Random Forest model performed moderately well due to its ability to reduce variance and identify important predictors. However, its tree-based structure limits its ability to model cyclical behaviour and long-term temporal dependencies, explaining its weaker performance relative to ANN. Meanwhile, ARDL showed limited accuracy because its linear structure cannot account for nonlinearities in healthcare spending. VAR performed worst because high-dimensional systems with multiple cost drivers reduce its stability and forecasting precision.

The findings suggest that machine learning models, particularly ANN, are well suited for forecasting medical inflation in modern healthcare systems characterised by price volatility, rapid technological change, and structural shifts. Policymakers, insurers, and risk managers may adopt ANN-based forecasting to support premium pricing, budget allocations, and healthcare financing strategies.

4.7. Forecast using Best Model

Through the ANN model, the projected HCI from 2025 to 2030 shows a clearly cyclical trend with a degree of volatility and a clearly identifiable cyclical variation over time. Inflation was expected to begin at approximately 2.6% in early 2025 and later fall quickly to its lowest level of approximately 0.5% by mid-2025. The rate of inflation, following this trough, was expected to increase sequentially in 2026, after which a high point of almost 1.8% will be reached at the start of 2027. The increase was followed by another dip to a seemingly 0.2% in early 2028. This was then followed by a gradual increase to a magnitude of approximately 1.2% in the first half of 2029, before a slight downward slope in the middle of the year. The rate of inflation

stabilises within a reduced range, with a narrow margin of 0.6 to 1.0%, between 2029 and the end of 2030.

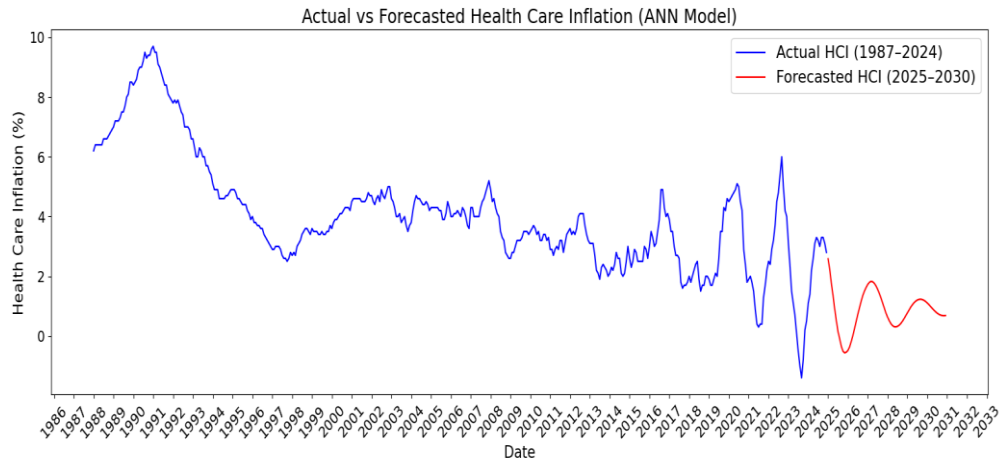


Figure 9: Actual and forecasted HCI using ANN

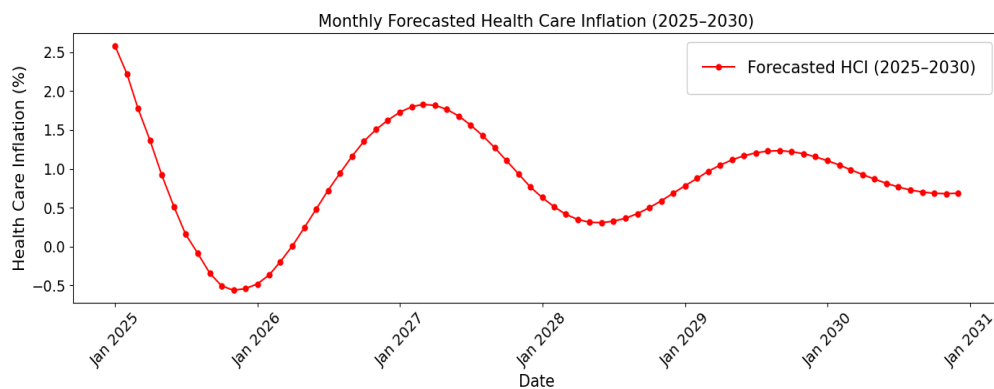


Figure 10: Monthly forecasted HCI using ANN

Such fluctuation refers to the situation where there will be times when costs increase and times when cost-cutting measures were implemented in the healthcare sector. The radical shift into the negative in late 2025 indicated a potential for a deflationary era to be followed by peaks of inflation. Generally, the forecasted dynamics indicate that, over the next five years, the amount of healthcare inflation is likely to remain within a range that could be deemed manageable. However, on occasion, slight deviations may appear due to seasonal factors, policy changes, or external influences that can cause fluctuations in prices in the healthcare sector.

5. Conclusions

This paper aimed to predict the nature of medical inflation in the US, with reference to the impacts of eight key components of medical costs: MC, Medical Care Commodities, Prescription Drugs, MCS, PMIS, PS, Dental Services, and HS. This selection was made because these variables had significant contributions to healthcare spending and were already included in the US Consumer Price Index (CPI) statistics. To meet the forecasting objectives of the study,

both established econometric frameworks, namely VAR and ARDL, and recent machine learning models, i.e., RF and ANN, have been used and evaluated.

Among all the tested models, the ANN demonstrated the best forecasting performance, characterised by the lowest prediction errors and the highest explanatory power ($R^2 = 0.8382$). This high level of accuracy indicates that the ANN model is effective in modelling non-linear relationships and seasonal dynamics, which are challenging to model with classical models. Although the VAR and ARDL models provided insightful results related to short- and long-run causality, they had to reduce variables to obtain stable results, thereby eliminating important predictors, such as HS, in the VAR. Conversely, machine learning models included all eight components, and they did not undermine the predictive integrity of the models. However, they did not affect model robustness.

The analysis has also highlighted those specific components of costs, particularly HS, Prescription Drugs, and PMIS, are major drivers that have impacted the future direction of medical inflation. Such evidence is essential to policymakers, health insurers, and health system administrators in designing specific cost-containment strategies and maximising the allocation of healthcare resources.

Although the methodological framework of the study was grounded in the US context, the study is also relevant in the context of Malaysia and other related healthcare systems due to similar pressures arising from rising healthcare costs, demographic transitions, and increasing demand for efficient allocation of limited healthcare resources. Malaysia has an ageing population, which is projected to reach 14.5 percent above 65 years old by 2040, there is expected to be a significant increase in the need for long-term care, as well as other high-cost medical services. Hence, the study will provide policymakers in Malaysia with a transferable and flexible forecast method that can be used to replicate the use of homegrown indicators of CPI-based healthcare rates. Both short- and long-run cost drivers are identifiable using traditional models such as VAR and ARDL. In contrast, more accurate forecasts of complex and non-linear trends are achieved on machine learning models.

Moreover, some issue areas that have been shown to cause inflation, such as hospital bills and prescription medicine prices, can be used to develop specific policies in Malaysia. These can include controlling hospital billing, encouraging the use of generic medications, enhancing transparency in pricing, and increasing funding in public healthcare. Ultimately, these measures may enhance the sustainability and affordability of the healthcare system.

Finally, this study successfully achieved its goals by examining the performance of medical inflation over time, the effectiveness of various modelling methods for forecasting medical inflation, and the most effective modelling method for predicting the movement of medical inflation. The combination of machine learning with econometric techniques offers a robust and flexible solution for estimating medical inflation. The knowledge gained through this study provides a valuable source of information for healthcare policymakers and planners in the US and in developing economies, where managing healthcare costs and achieving long-term sustainability are crucial.

Acknowledgments

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