CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of the significance of health expenditure prediction, machine learning in healthcare and health economics, existing models used for health expenditure predictions, determinants of health expenditure, research gap, and summary. This chapter aims to review existing literature on this study, evaluate the approaches to tackle the issue, strengths and limitations of each model, and analyse the research gap that has not been resolved in the current studies.

2.2 Health Expenditure and Prediction

Health expenditure can be represented by Total Health Expenditure (TEH), Current Health Expenditure (CHE), which excludes health-related expenditure (e.g., personnel training, research and development), General Government Health Expenditure (GGHE), and household Out-Of-Pocket health expenditure (OOP). (World Health Organization [WHO], 2025). In 2018, global spending on health achieved USD 8.3 trillion, which is 10% of global GDP. On average, low-income countries spent 6.4% GDP on health, lower-middle income countries spent 4.8%, while upper-middle income countries spent 6.3%. (WHO, 2020).

Health financing in Malaysia is largely funded by public funding (RM 41,257 million), which consists of 52.3% of total health expenditure, followed by private sources of financing, accounting for RM 37,688 million (47.7%). The TEH of Malaysia is gradually increasing from 2011 to 2022, showing more than 2-fold increase from RM 35,953 million (3.94% as GDP) to RM78,945 million (4.41% as GDP), and a significant increase can be seen in 2022 compared to pre-COVID-19 pandemic value (Ministry of Health Malaysia, 2024). Despite that, public spending on health remains lower when compared to the average 6.3% of GDP spent in middle-income countries (WHO, 2020). Low public health spending may contribute to a range of issues like chronic understaffing, high workload, and critical infrastructure shortages. At the same time, rising OOP payments and increased pharmaceutical costs create a potential risk to the healthcare system, justifying the need for economic evaluation for health policy planning (Khor et. al, 2024).

Household OOP includes health spending by people for the services of curative care in private, public hospitals and clinics, purchase of pharmaceuticals (over-the-counter and prescription drugs), health education and training, medical appliances and non-durable goods, daycare services, traditional and complementary medicine. (Ministry of Health Malaysia, 2024). Catastrophic health expenditure, which is defined as OOP exceeding 10% total household consumption, is on a trend of rising based on a study by Sayuti & Sukeri (2022), from an estimated 1.44% in the household expenditure survey 2004/2005 to 2.8% in 2015/2016. The authors conclude that vulnerable groups' access to healthcare services should be improved to avoid the vicious cycle of debt due to rising healthcare costs. The conclusion is supported by the result of a study by Wan Puteh et al. (2023) on the cancer population in Malaysia, which revealed that 54.4% of respondents in their study experienced catastrophic health expenditure. This signifies the importance of well-planned healthcare budget allocation by policymakers.

Prediction models are highly beneficial and practical for determining the sectors where the spending is growing and reveal the driving factors for the health expenditure. Short-term predictions have better accuracy in forecasting future events, but limited action can be taken to change the prediction. Medium to long-term estimation excels in its ability for policy-planning and decision making because they can identify future trends where policy makers can shift the outcomes trajectory (Astolfi et al., 2012).

Ku Abd Rahim et al. (2020) conducted a systematic review on the economic evaluation of healthcare in Malaysia and highlighted that publications related to health economics are sparse and inadequate to meet stakeholders' and policymakers' needs. There are challenges in collecting cost data and the availability of data that need to be addressed, and the authors suggested that data modelling studies can address this issue.

Various attempts have been proposed to improve health expenditure allocation. The prediction of how total health expenditure and its sub-components change contributes significantly to evidence-based policy making. While an increase in health expenditure may translate into better health outcomes for the people, it is crucial for policymakers to closely monitor and address issues of health spending to avoid a significant burden on public resources while ensuring individuals' access to affordable healthcare services.

2.3 Machine learning in healthcare and health economics

Machine learning is a subset of artificial intelligence, apply computational algorithms to construct and fit statistical models using available real-world data. It aims to estimate outcomes or assigning categories to the input data provided based on training (Rubinger et al., 2023). Application of artificial intelligence and machine learning in healthcare research is rapidly expanding, from utilizing data from electronic medical records for clinical decision-making to estimating the cost of treatment using patient-level factors, owing to the increased availability of big health data.

Lee et al. (2022) conducted a systematic literature review on the use of machine learning techniques in health economics and outcomes research (HEOR). The authors identified that machine learning is useful in predicting clinical events or disease occurrence, treatment outcomes, health resource utilization, and costs. The study concludes that tree-based methods are the most commonly used machine learning techniques, followed by logistic and linear regression, support vector machine, and neural network.

However, the applications of artificial intelligence and machine learning in healthcare do encounter ethical challenges and privacy-related issues, like patient data protection. Moreover, the lack of high-quality data for training and evaluations may cause performance issues in forecasting and may introduce bias (Wubineh et al., 2024). Therefore, healthcare data must be handled carefully by complying with the legal and regulatory framework while ensuring anonymity and security of the data. In addition, data quality must be assessed before applying any machine learning model to ensure its accuracy and reliability.

Nonetheless, there are lots of opportunities in the application of data science techniques, including machine learning in healthcare, for instance, personalized medicines, real-time monitoring, disease prevention, and diagnosis. By using predictive analytics and focusing on cost savings, initiatives can be taken to improve patient access to affordable healthcare services, reduce healthcare costs, improve efficiency in the healthcare system, and ultimately improve patient outcomes (Devi & Bansal, 2024).

2.4 Existing Models used for Health Expenditure Prediction

This subsection compares existing models used for health expenditure projection, which include different machine learning methods and traditional statistical models. Machine learning algorithms included in this subsection are Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network, and Random Forest (RF). Traditional statistical approaches, Grey Model (GM), and Exponential Smoothing Model (ETS) are included for comparison.

2.4.1 ARIMA

ARIMA model is one of the most used time series forecasting techniques. It is a model that consists of three components: autoregressive (AR), integrated (I), and moving average (MA). The Autoregressive (AR) part is a regression model that focuses on using past data points (lagged observations) to predict future values. The integrated (I) part aims to make the time series stationary by performing differencing to eliminate trend and seasonality. The moving average (MA) part focuses on the dependence between observations and the residual errors. It captures meaningful short-term changes and removes random noise from the time series.

Application of ARIMA model for predicting health expenditure 5 years forward has been done in China by Zheng et al. (2020), which predicted not only total health expenditure but also its constituent ratios of GHE, social health expenditure (SHE), and OOP by using time series data from 1978 to 2017. Social health expenditure refers to the basic medical insurance fund collected by various social medical insurance projects. SHE is expected to grow the fastest in China which will decrease the proportion of GHE and OOP.

A similar approach was done using ARIMA for the BRICS (Brazil, Russia, India, China, South Africa) countries to forecast until 2030. The authors projected total health spending per capita and total health spending as a percentage of GDP for these countries. Estimation of government, prepaid private, and OOP has been done from 2018 to 2030. (Jakovljevic et al., 2022) However, the authors reported that despite ARIMA providing useful forecasts as a time series model, the results have high uncertainty in values due to a large prediction interval, data quality issues like measurement error and imputation, lack of an obvious pattern and trend in some of the datasets.

Kontopoulou et al. (2023) have reviewed ARIMA versus machine learning approaches and deep learning methods for time series forecasting in financial, healthcare, and various other sectors. The authors outline that ARIMA has advantages like being more explainable, flexible, and reliable, performs better for small datasets or for short-term forecasting, has low time complexity, and smaller computational requirements. However, ARIMA do comes with limitation like difficulty in forecasting complex real-world problems due to its univariate modelling approach and is more sensitive to outliers.

2.4.2 Artificial Neural Network

Artificial neural network (ANN) is a machine learning model that simulates networks of biological neurons in the brain. Artificial neurons are arranged in layers and build up a neural network to mimic the human brain. ANN is formed by input layers, output layers, and one or multiple hidden layers in between. Deep learning algorithms refer to the use of neural networks formed by dozens to hundreds of layers to process large and highly complex tasks, for instance, classifying billions of images, powering recommendation systems for e-commerce, and developing strategies in chess and games. (Géron, 2022). The algorithms can perform feature engineering automatically where the features in the dataset are searched and correlated without human intervention. (Ahmed et al, 2023)

Adaptive Neuro-Fuzzy Inference System (ANFIS) and Hybrid Neural Fuzzy Inference System (HyFIS) are implemented to predict the health spending in Jordan. Both models demonstrated their capability in predicting total health expenditure accurately, with HyFIS outperformed ANFIS. (Saleh et al., 2023) Notably, five variables used in the neural network in this study demonstrate the capability of the neural network to obtain accurate prediction results based on multiple inputs.

Ahmed et al. (2023) suggested that training a deep learning model is time-consuming, computationally expensive, and requires large samples or training data to achieve better accuracy. It also demanded improved optimization of the parameter to create a more robust model. Deep learning techniques are regarded as “black boxes” because their interpretation is difficult. Their architectures are highly complicated, and the decision-making process is not made clear to the user.

2.4.3 Random Forest

Random Forest (RF) is a machine learning algorithm that ensembles the output of multiple decision trees to obtain a prediction outcome. It can be used for classification and regression problems. Each decision tree starts with a root node that branches into several decision nodes, which are made up of a set of questions. The decisions made at those nodes based on input data will lead to the leaf nodes which are the terminal node that shows predictions.

Random Forest utilizes bootstrap aggregating and feature randomness to create an uncorrelated forest of decision trees. Bootstrap aggregating refers to random sampling with replacement of the original dataset to train each decision tree. Feature randomness means a random subset of features is selected at the split of each tree. This can reduce the risk of overfitting, bias, and overall variance, which provides more accurate results compared to a decision tree used alone. (IBM, n.d.)

Wang et.al. (2024) compared RF, Support Vector Regression (SVR), and ARIMA in forecasting US healthcare expenditure as a percentage of GDP to 2050. The authors revealed that RF and ARIMA yield comparable results (18.8% and 17.9% respectively) when trained with time series data, while SVR struggles to learn effectively with limited data. The authors proposed that healthcare expenditure is affected by multiple factors, therefore, further investigation into the interaction among the factors (e.g. demographics, technology, and political landscapes) can provide a more comprehensive analysis.

Muremyi et. al (2020) conducted research on OOP health expenditure in Rwanda using a tree model using 14 independent variables from household conditions at the micro-level. The authors suggested that while the machine learning approach is criticized compared to traditional statistics due to model assumptions, they do offer better generalization capability and are effective for selecting predictable features from the datasets.

Another study compared 5 AI-based forecasting models (RF, ANN, Multiple linear regression (MLR), SVR, Relevance Vector Machine (RVM)) to predict healthcare expenditure per capita in Turkey and concludes that the combination of genetic-algorithm feature selection and random forest demonstrated the best prediction performance in the study. (Ceylan & Atalan, 2020). The authors suggested that RF predicts better than single base learners and is less prone to overfitting than other machine learning algorithms. It also works well with large datasets with many input variables and missing values, which contributed to higher performance.

2.4.4 Other Statistical Models

Among the research of health expenditure prediction, various other traditional statistical model other than machine learning was used, which can be contrasted with machine learning for their advantages and limitations. The common approaches from recent literature are the grey model and the exponential smoothing model.

Grey model is a time series forecasting equation that is constructed based on past and present known or uncertain information. It is often used in economic analysis. The model is represented as GM (M, N), where M is the derivative order and N is the number of independent variables. Li & Zhang (2024) used the univariate grey prediction model GM (1,1) to predict the trend of total health expenditure and the share in GDP in China, which is expected to increase continuously and reach 8.89% of GDP by 2030. A small amount of data is needed for this model, and there is a low data distribution requirement. The study limitation is that the model used is univariate; therefore, other factors affecting the prediction are not considered.

Jia et al. (2021) performed a New Structure of the Multivariate Gray Prediction Model NSGM (1, N) to predict health expenditure in China and compared it against the traditional grey model and back propagation neural network for evaluation. The authors evaluated 9 driving factors of health spending using grey correlation achieved better prediction accuracy than other models with limited data. However, the authors noted a limitation where the prediction performance of the model might be influenced by the correlation between the variables used.

Sahoo et al. (2023) conducted time series analysis and an exponential smoothing model (ETS) on BRICS countries to predict health expenditure and its components to 2035. ETS predicts by assigning high weight to the nearest outcomes over time, and the weights of older observations decrease exponentially. ETS considers error, trend, and seasonal components of the time series data and evaluates 30 alternative models before deciding the best-fitting model. The model comes with limitations like limited incorporation of external factors and the assumption of continuity in historical patterns.

2.4.5 Discussion

Strengths and weaknesses of each model described in the literature are tabulated in Table 2.1. For traditional statistical models and ARIMA, the computational requirements are smaller, the model is less complex, thus offering improved explainability. These models are able to provide reliable results with a limited amount of data. However, the model faces limitations in handling large, complex, and multivariate data, which limits their ability to solve real-life complex problems. The prediction terms are usually shorter compared to machine learning techniques.

On the other hand, random forest and artificial neural networks are able to incorporate a large amount of data, which is especially useful in predicting health expenditure that is affected by multiple driving factors. Non-linearity in the data can be captured as well. Nonetheless, the models also come with weaknesses like large computational requirements and consume more time. Due to the increase in model complexity, the interpretability of machine learning techniques is lower.

Table 2.1: Summary of the strengths and limitations of the model

Model	Strength	Limitation	References
Autoregressive integrated moving average (ARIMA)	• Explainability • Flexibility • Better performance for the small dataset • Suitable for short-term forecasting • Smaller computational requirements	• Univariate modelling • Vulnerable to changes in other fields • Difficulty in forecasting complex real-world problems • More sensitive to outliers • Uncertainty if the prediction interval is large	(Zheng et al., 2020), (Jakovlje et al., 2022), (Kontopoulou et al., 2023)
Artificial Neural Network	• Able to manage large and complex data • Non-linear time dependencies • Can combine the forecasts of multiple time series	• Require a large amount of training data • Require optimization • Computationally expensive • Time-consuming • Low explainability	(Kontopoulou et al., 2023), (Ahmed et al, 2023)
Random Forest (RF)	• Able to incorporate multiple factors • Less affected by missing values • Lower risk of overfitting and bias • Lower overall variance • Better generalization capability	• Computationally expensive • Higher memory usage • Time-consuming • Less interpretable than an individual decision tree	(Wang et.al., 2024), (Ceylan & Atalan, 2020), (Muremyi et. al, 2020)

Table 2.1: Continued

Grey Model (GM)	• A small amount of data is needed • Low data distribution requirement • Predict better than a back propagation neural network when the data is fewer	• Poor long-term forecasting • Univariate prediction model does not capture complex patterns in data • Prediction performance of a multivariable model may be affected by the correlation among variables	(Li & Zhang, 2024), (Jia et al., 2021)
Exponential Smoothing Model	• Gives higher weight to the nearest outcomes over time • Automatically select the best-fitting model based on data error, trend, and seasonal components	• Limited incorporation of external factors • Assumption of continuity in historical pattern	(Sahoo et al.,2023)

2.5 Determinants of health expenditure

There are two distinct approaches in the prediction of health expenditure observed from the current literature. One approach is by conducting time series analysis, which is based on time series data of health expenditure using lagged variables (past value) of the dependent variable. Another approach involves the incorporation of the determinants of health expenditure, such as GDP, demographics, the number of hospitals and physicians, through econometric analysis. As health expenditure is affected by multiple drivers, the latter has improved forecast accuracy and is able to project long-term spending. It also allows policymakers to test "what-if" scenarios of new policies and recalculating future expenditure estimation.

Among health spending prediction models discussed above, macro-level models like time-series analysis that focus on total health expenditures are useful for short-term projection when trends are well-defined and uninterrupted. Forecasting models that analyse health spending using the sub-components in health expenditures or other determinants of health expenditures are more flexible but require more training data for forecasting. The determinants of health used in the studies are summarised in Table 3.2 below. It can be seen that determinants used as independent variables in the research vary depending on the researchers and their country of study, but some common elements can be found among them, which include GDP, the number of physicians and hospitals, and population over 65 years old.

In the context of Malaysia, Khan et al (2016) propose that GDP per capita, population growth, population structure, and technology have a positive influence on healthcare expenditure by using the Autoregressive Distributed Lag (ARDL) approach, which is an econometric model to analyse the relationship between time series data. Yap & Selvaratnam (2018) use a similar approach and suggested that per capita GDP, healthcare price index, population aged more than 65 years, and infant mortality rate are important determinants for public health expenditure in Malaysia.

Table 3.2 Determinants of Health Expenditure

References	Determinants of Health Expenditure	Data sources
(Ceylan & Atalan, 2020)	GDP per capita, Life expectancy at birth, Unemployment rate, Crude Birth rate, Number of hospitals, and Number of hospital physicians	OECD library
(Saleh et al., 2023)	Number of physicians, the number of beds in hospitals, the population size, and the consumer price index	World Health Organization (WHO), Jordan's Ministry of Health, Central Bank of Jordan.
(Jia H. et al, 2021)	Number of people aged 65 and over, Population, GDP, number of medical technical personnel, number of beds in healthcare institutions, general government expenditure on health, out-of-pocket health expenditure, infant mortality rate, household consumption expenditure.	National data from the China Statistical Yearbook and the China National Health Accounts Report
(Lorenzoni, 2019)	Percentage of population over 65 years old, GDP per capita elasticity, Baumol coefficient (wage over productivity), technology progress (country research and development spending as a share of GDP), and mortality	National sources of the countries in the OECD and the Eurostat HEDIC report

2.6 Research Gap

Several research gaps were discovered in the literature review process. Firstly, there is limited academic research on Malaysia's health expenditure forecasting despite rising needs. In contrast, many countries have research on health expenditure using advanced forecasting techniques to support health financing decisions. The application of a predictive model by using open data sources in Malaysia to forecast future health expenditure could address the gap. By leveraging time series models and machine learning algorithms, this study can support policy decisions and improve financial planning in healthcare.

From the literature, it is shown that health expenditure is affected by multiple factors and traditional statistical models struggle to capture complex and non-linear relationships. Machine learning techniques can offer improved multivariate forecasting accuracy in health expenditure. Comparison of performance metrics between the models used can be made to determine the best model.

Lastly, different determinants or independent variables of health expenditure are used in the studies from different countries, and there is no general consensus between studies on which determinants to include. This can be addressed by comparing determinants of health expenditure in global and local economic studies. The selected determinants' correlation with health expenditure in Malaysia will need to be analysed before applying them to the prediction model.

2.7 Summary

This chapter discusses the challenges of health spending in Malaysia and highlights the research gap where publications on prediction models for health expenditure are limited. Several machine learning approaches to forecast health spending are reviewed, with their respective strengths and limitations outlined. The determinants of health expenditures used in the previous studies are compared and contrasted with local Malaysia research to propose relevant factors for the prediction model.

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