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Integrating Machine Learning (ML) and Artificial Intelligence (AI) Applications into Health care financing for Achieving Universal Health Coverage (UHC) for Egyptian Health Care system: Literature Review.

By

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Abstract

Over the past decades, Egypt has made significant progress toward improving the health outcomes of its population through the implementation of the Universal Health Insurance (UHI) Law enacted in 2018. The implementation of the new UHI Law of 2018 requires a major transformation to the health financing system. In addition to, it is essential to move into the digitalization age of healthcare in Egypt.

Artificial Intelligence (AI) and Machine Learning (ML) tools have the potential to improve the efficiency of healthcare system, decision-making processes, and optimizing healthcare financing systems. Additionally, AI applications can also set priorities for the resource allocation of governments that are involved in achieving Sustainable Development Goals (SDGs).

This study provides an overview of the integration the Machine Learning (ML) approaches into healthcare financing functions to overcome the issues related to the health financing system that accelerate achieving UHC in the Egyptian health system.

To achieve this objective, the researchers used a systematic Literature Review by reviewing full papers, charting extracted data, and screening and summarizing findings. This Literature Review was done through the database of PubMed, Google Scholar, Scopus, and Web of Science from January 2000 to December 2023.

This research revealed that ML and AI applications have a significant impact on many aspects of the health financing domain in the Egyptian health system that supports health Digital Transformation and the role of E-Health Company, the first health digitalization company in Egypt for progress toward UHC in 2030.

Additionally, it proposes some recommendations related to Egyptian health financing system and regulatory framework of AI risks based on ML algorithms, Also it recommends the integration of both public and private healthcare data in order to accelerate the UHC of the Egyptian healthcare system.

Keywords:

Artificial Intelligence (AI), Machine Learning (ML), Health Financing System, out of pocket payments, Healthcare system.

1. Introduction

1.1 Background

Health insurance is one of the interventions as one of the ways to achieve UHC. Recently, there has been growing interest in the application of intelligence AI and ML algorithms in healthcare. AI and ML applications will likely improve access to healthcare; optimize the resources allocation, thus helping health systems function more effectively and efficiently. In other words, ML /AL applications have the ability of reshaping the healthcare system.

The goals of healthcare systems are constantly evolving as new technologies and knowledge become available. However, the overall goal of improving the health of the population remains the same.

Egypt is the largest market in North Africa and Middle East. The Egyptian healthcare system has multiple stakeholders such as: public and private healthcare providers, financing agents, and financing sources. *(Fasseeh et al., 2022)*

Egypt has achieved a progress toward improving the health indicators of its population over the last decades as shown in table (1), increasing the overall life expectancy has from 64.5 to 70.5 years over. Also, the Egyptian government has launched many public health initiatives such as early of anemia, and stunning, and elimination of Hepatitis various C. *(GlobeMed Egypt, 2023)*

Table (1): The key Health Indicators for Egypt and MENA region

	2012		2015		2019		2020	
	Egypt	MENA	Egypt	MENA	Egypt	MENA	Egypt	MENA
Life expectancy at birth	70.4	70.8	73.2	70.9	71	69.7	71	--
Infant mortality (per 1,000 live births)	17.9	27.8	20	25	17	18	17	18
Maternal Mortality Ratio (per 100,000 live births)	42	60	39	59	--	--	--	--
DTP3 Immunization Coverage	93%	78%	93%	80%	95%	85%	94%	81%

Source: World Bank,2021

The Egyptian SHI coverage is provided through the health insurance organization (HIO). According to HIO report 2012/2013, HIO covers 58% of the population, it represents as both service purchaser and provider through health facilities and operate its own primary care, in addition to some secondary and tertiary care services it owns. The majority of the population under HIO coverage (74%) is schoolchildren and infants. The smallest bulk (6%) is widows and pensioners, the reaming 20% of insured are from the active work force.

The ministry of health and population (MOHP) and other government's agencies operate a nationwide network of government health care providers, primary, secondary and tertiary and provide free or substantially subsidized health services to the citizens not covered under HIO. *(Khalifa et al ,2021)*

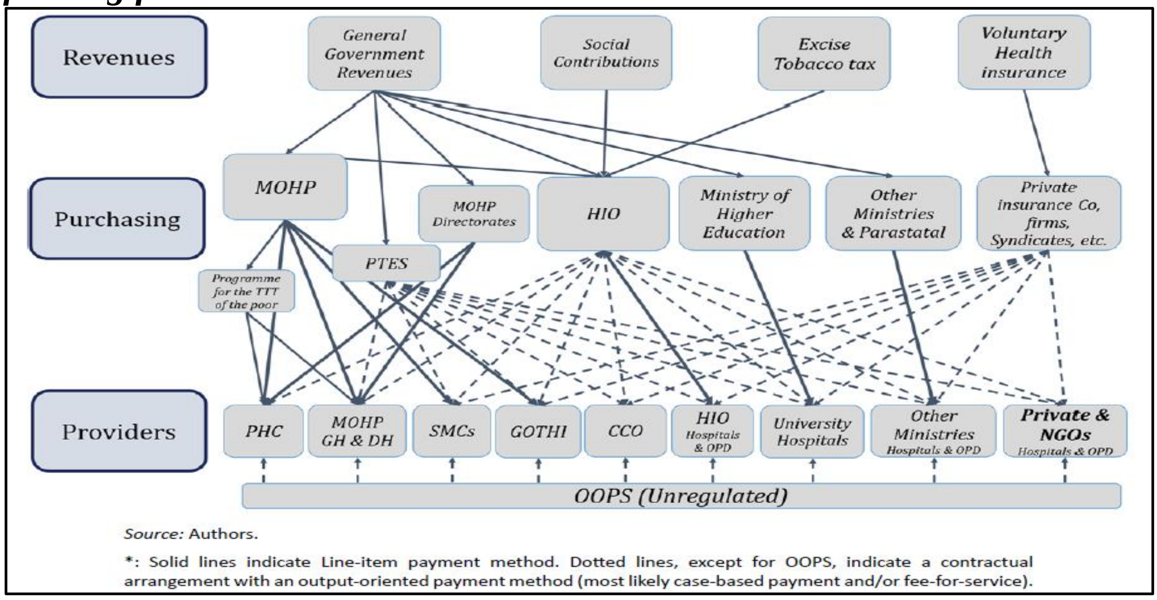
Although these improvements in health system in Egypt, there is a need to increase in demand of health services of 16-35% per year with the increased demand for complicated, sophisticated and high-quality

services. In Addition to, the Egyptian health system cannot target the poorest people to reduce the poverty and out-of-pocket (OOP) expenditures by providing basic health care services to all. *(Fasseeh et al, 2022)*

Egypt's healthcare financing sources can be categorized as household payments (OOP), Government sector, Public sector, and Private organizations. OOP payments have consistently remained the largest source of health financing in Egypt for all levels of care, with an adoption of the "fee-for-service". This system requires households to pay at the point of care in both private and public health facilities, placing a significant financial burden.

Figure (1) illustrates the healthcare service providers in Egypt receive funding from multiple streams, which align with the inconsistency in healthcare cost and quality across providers *(Mathauer et al , 2019).*

Figure (1): Current health financing system architecture and funding flows



Source : *Mathauer et al , 2019*

In 2018, the Egyptian parliament adopted the new universal health insurance law No.2, as part of sustainable development Strategy Vision 2030 in Egypt, promising to provide comprehensive healthcare coverage for all Egyptians. It established the Universal Health Insurance Authority as an independent agency to merge all insurance pools (public and private) into a single pool and introduce new roles for private health insurance. Additionally, ensuring access to quality health services without financial hardship for all Egyptian citizens, offering adequate and sustainable, reducing OPP expenditures through an integrated health system reform and the introduction of a compulsory social health insurance scheme. ***(World Bank,2020)***

Therefore, the health sector in Egypt requires expanding rapidly and making decisions for both investors and health facilities providers. To reduce the current and potential financial demand gap, it is invertible to move into the digitalization age of healthcare in Egypt.

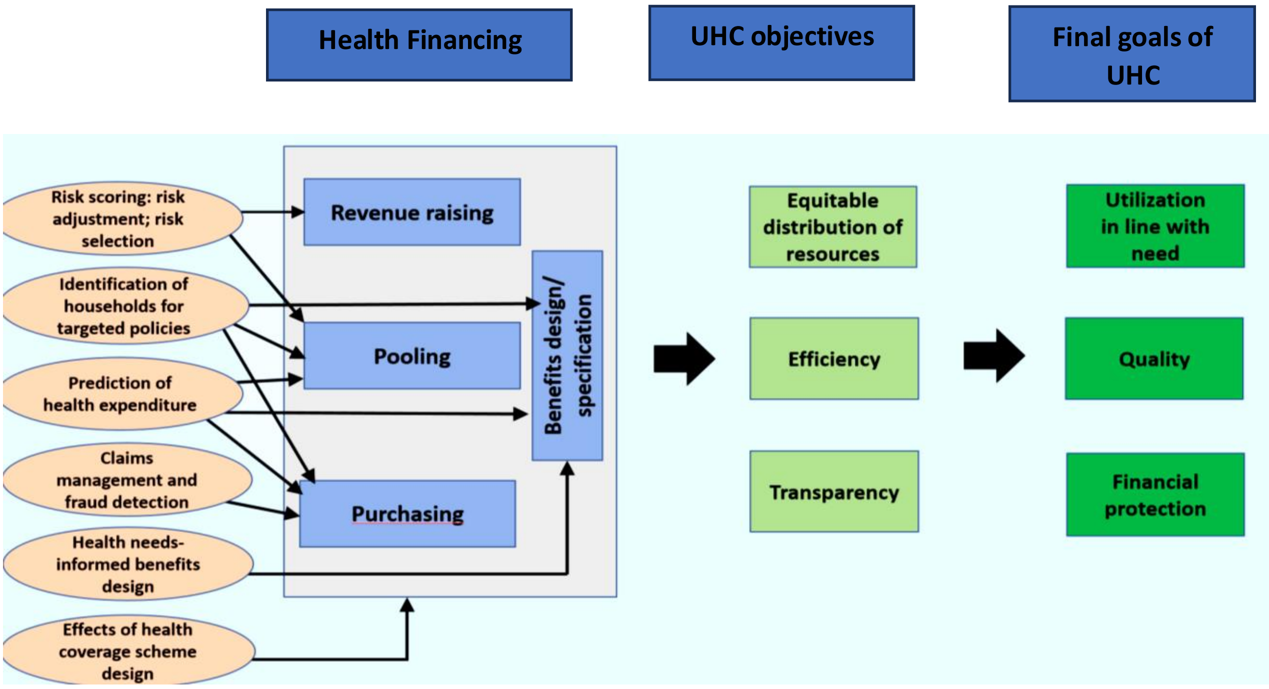
Monitoring UHC framework requires tracking the level of the financial protection in providing healthcare services, which is the incidence of catastrophic health expenditure and the poverty due to out-of-pocket health payment. This represents a major challenge within the Egyptian healthcare financing system.

There are six categories of health financing functions that relate to using ML and AI applications as the objectives of universal health coverage (UHC). These categories are classified into: Forecasting health expenditure, risk scoring, claims management and the health claims frauds detection, Priorities of the benefit package design, and analysis of the impact of design health coverage scheme on health service utilization. ***(WHO, 2023)***

Generally, ML requires big and high-quality and privacy security data in order to achieve optimal outcomes that are both tangible and reliable.

<u>The following figure (1) outlines the linkages between machine learning models, health financing domain and UHC objectives goals.</u> In conclusion, it can summarize following effects of the digitalization for health financing and UHC purposes.

Figure (2): The relationship between the ML models and final goals of UHC



Source: by the researcher

The above figure illustrates how ML Applications, integrate into health financing functions, enhancing intermediate and final UHC goals. ML applications and health digital transformation have the ability to enhance health Financing policy design, and effectively achieving Egypt's' health sector UHC by 2032.

1.2 Implications of the New UHC Law:

Egypt's Universal Health Insurance (UHI) Law of 2018 implies significant major transformations and improvements in the Egyptian health system that leads to acceleration progress towards UHC, providing UHC goals of equitable resource use, efficiency, transparency, accountability, financial protection, and quality care.

To assure that Health financing reforms have a good influence on enhancing delivery to health care and financial protection, it is equally important to ensure that all aspects of the reform are aligned, even while a legally binding mandate is necessary to develop health finance and purchasing changes. In addition to, ensuring available healthcare services to the whole population regardless of their income level. As a result, the new 2018 Universal Health Insurance law was enacted to reform the healthcare system in alignment with Egypt's 2030 Sustainable Development Strategy. (GlobeMed Egypt, 2023)

Improving health care financing efficiency can be achieved by increasing the public financing and reducing financial fragmentation through UHI implementation.

The new UHI law aims to reduce high out-of-pocket payments and catastrophic health expenditures by enrolling all family members in the insurance program. Due to limited available resources, UHC for all Egyptians will be categorized into over six stages, concluding by 2032. Given limited available resources, providing comprehensive health care coverage for all Egyptians in a one stage is a challenging task. ***(Fasseeh et al., 2022)***

The undertaking which is partially funded by $400 support package from the world bank, was launched with a pilot project in port said in July 2019, By December 2022, it is estimated around 2.7 million

residents of port said, Luxor , and Ismailia have been enrolled in the new system that is expected to be completed by 2027.

Upon completion, the UHI budget will significantly increase the total health expenditure (THE) as a percentage of GDP. The system will feature a split between payers and service providers, encouraging competition and improving service quality. Both public and private providers can join the new system, fostering competition and improving patient care. A good competition among healthcare providers typically results in improved quality of care. It empowers patients in their interactions with providers and helps align services with patient needs while efficiently allocating resources. Conversely, when patients are restricted to specific health facilities, competition is absent, leading to a lack of incentive for providers to enhance their services. When patients can access good quality healthcare facilitates, the lower quality facilities will eventually offer better services to attract patients and thus generate revenues. ***(Angelis et al, 2017)***

This reform aims to address the healthcare system's challenges, including underinvestment and inefficiencies. ***(Khalifa et al. , 2021)***

Currently, out-of-pocket payments (OOP) constitute about 62% of health expenditure, with government spending at around 29%. Additionally, 3.9% of the population faces severe catastrophic health expenditures, and 1.07% is impoverished due to OOP. Table 2 outlines health expenditure indicators, highlighting the need for increased government health spending.

Table (2) : Health Expenditures Profile in Egypt

	2000	2006	2012	2019
Health spending $US per Capita (CHE)	74	71	151	150
% Government Health Spending (as share of CHE)	35.2%	36%	28.7%	27.8%
% OOP Spending (as a share of CHE)	62.5%	60.4%	60.9%	62.7%

Source: Globe Med Egypt, 2023

The healthcare financing system in the previous law was fragmented, with multiple purchasing with multiple purchasing actors and varying coverage schemes for different population groups, leading to unequal benefit packages, undefined ceilings for medication costs and payment methods. For example, The HIO, a major public insurer covering 60% of the population, operates several separate fund pools for different groups, such as civil servants, retirees, widows, and children, with limited cross-subsidies between these groups.

UHC is filling the gap between what the health system should be and what it does. This can be achieved through translating UHC goals into two questions as shown in the following table (3): What services and policies should be implemented? What challenges in these implementations that need to be more effective? *(Alami H, 2020)*

Table (3): Key indicators of significant changes introduced by new Law

	The significant improvements according to the new LAW UHC	**The Remaining challenges**
Benefits	The UHC law outlines a clear benefits package, aiming to define the scope of services explicitly.	1. Criteria for prioritizing health services in the benefits package is unclear. 2. Prevention and early detection are covered by the MOHP, not included in the UHI package.
Cost-Sharing - mechanism	1. Cost-sharing rates have been minimized, with a cap on for medications, diagnostics and inpatient services. 2. Poor and people with critical illness are exempted.	1. For medications, the period for the cap amount is unclear. 2. The list of critical illness and their related medications are not defined.
provider payments	The provider payment mechanisms are independent of the government.	The law doesn't provide the details of procedures foe setting and revising the payment methods.

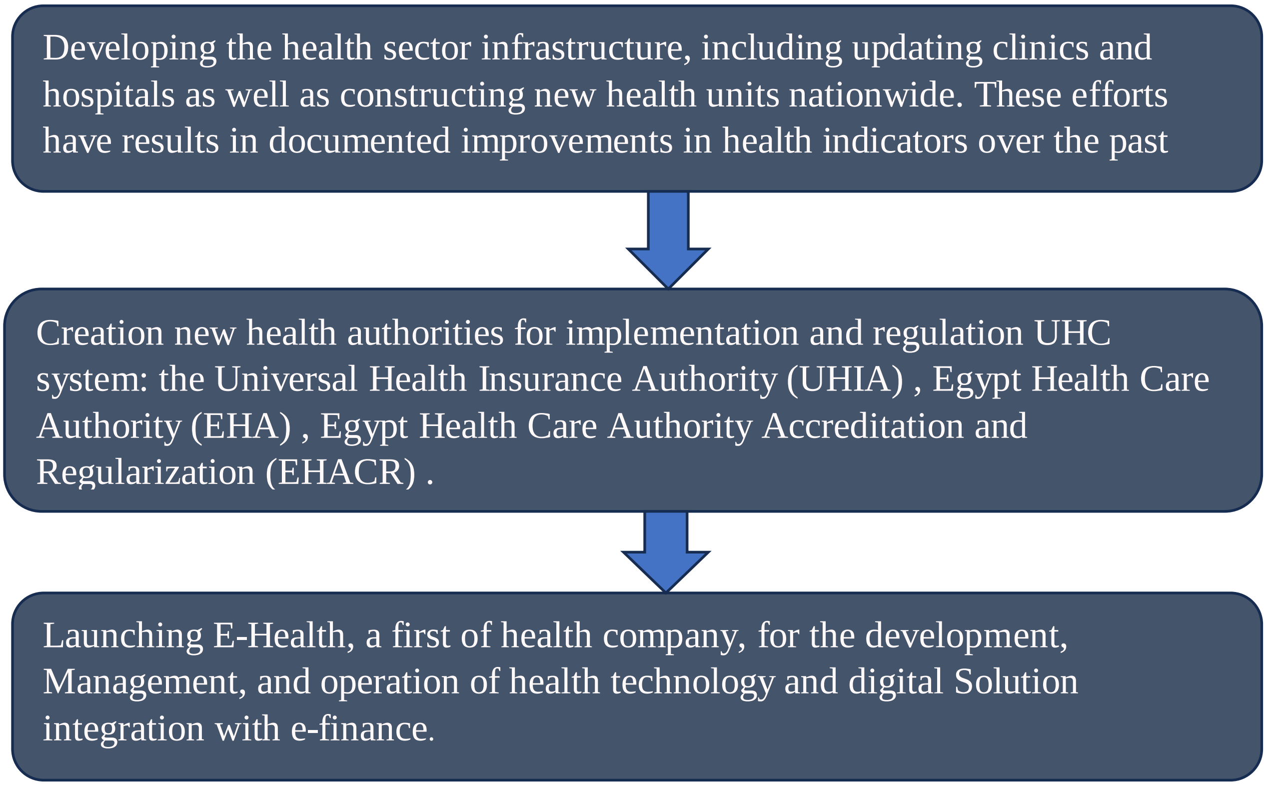
Source: Kalifa etal.,2020

To overcome the challenges that face implementation the new law UHI, the implementation needs digitalization transformation of health sector and using AI /ML applications.

The experience of Egypt shows that it is possible for middle -and -low-income countries achieved UHC to cover all populations, even large proportion of the population live in rural areas.

The key achievement of the implementation of universal health insurance system in Egypt will result significant improvements in the upcoming years. Since the start of the implementation of UHC system starts in Port Said, significant progress has achieved as shown in the following figure. (GlobeMed Egypt, 2023)

Figure (3): The significant achievements toward achieving UHC



Source: By the researcher

This paper will discuss number of ML techniques in health financing. To address health problems related to financing in the Egyptian health system, ML applications should be used and enhanced. ML algorithms can transform health care financing, processes, and policy-making. Despite the risks arise from using AI in healthcare systems, such as preserving patient privacy data and ethical standards, its potentials are documented in this research. To enhance outcomes in health financing and make the implementation of new Law of UHC more effective, the policymakers need to integrate ML applications into their decision-making processes.

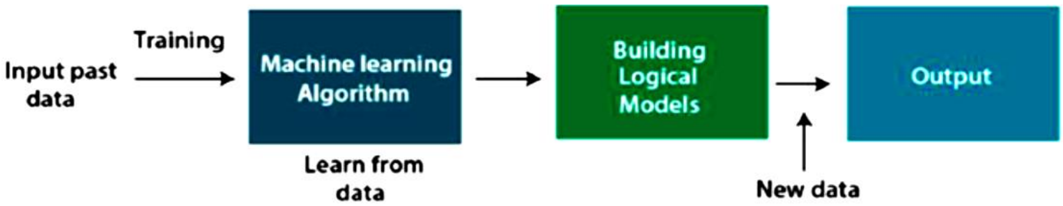
1.3 Machine Learning

ML is a rapidly involves technology and a subfield of AI. It is combination of statistical and mathematical modeling techniques, whereby algorithmic models are trained to data train patterns, and to make predictions based on the test data without any interference. The validation data helps to construct a better model that predicts the model more accurate. As mention before, ML is a subfield of AI that concerns the methods which learn to perform prediction or classification based on available data. Additionally, ML has significant role in analyzing big data, which are too complex data sets for traditional data processing methods. The main advantage of using ML that it results in the higher accuracy and enhanced prediction performance compared with traditional statistical models, as data processing and analysis can be automated. This has potential in reductions in administrative cost for the providers of health financing, such as purchasers, providers, In Particular, claims management and

fraud detection. Therefore, ML applications have significant role in health financing. (Shanthi et al, 2023)

The following figure (4) illustrates the sequences of ML algorithms to make a prediction.

Figure (4): The sequences of ML algorithms



Source: Shanthi et al, 2023

<u>The main common algorithms of machine learning are:</u>

1. <u>Supervised learning</u>, where the data used to train a model are structured and the target variables are known, supervised learning algorithms can be used for classification problems, regression problems and prediction problems. The common supervised learning models are: Generalized linear Model, logistic regression, Bayesian networks, and the tree-Based Models.
2. <u>Unsupervised learning</u>, which does not involve in structured data but helps in exploring the hidden patterns in the data that illustrated the relationship between the target variables and the predictors based on grouping and clustering of the data points. The main approaches of unsupervised techniques problems are: Clustering problems, and highly linearity problems. The unsupervised learning techniques are: hierarchical and K-means clustering, and Principal component Analysis (PCA).

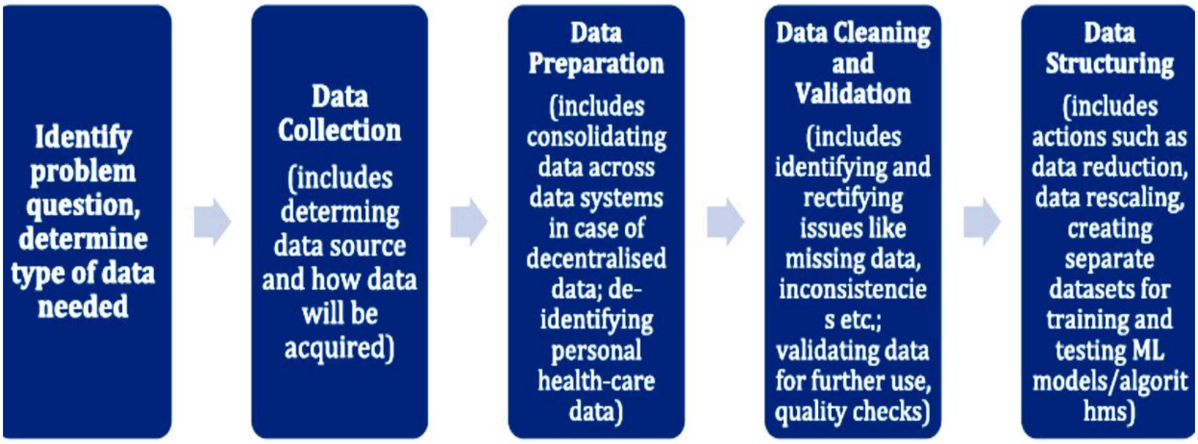
Clustering techniques have potential in heath sector for providing solutions for health decision-makers to monitor insurance coverage based on the features of socioeconomic, geospatial, and demographic.

3. **Semi-supervised learning, which is hybrid algorithms of both supervised and unsupervised learning algorithms. This type involves a small amount of structured data is combined with a large amount of unstructured data.** (National Health Authoriety , 2023)

Generally, the supervised and unsupervised learning techniques are sometimes used in conjunction with one another. Unsupervised learning techniques can be used for the purposes of data exploration and producing potentially useful features for predicting the target variables more accurately. ***(Dairi et al., 2021)***

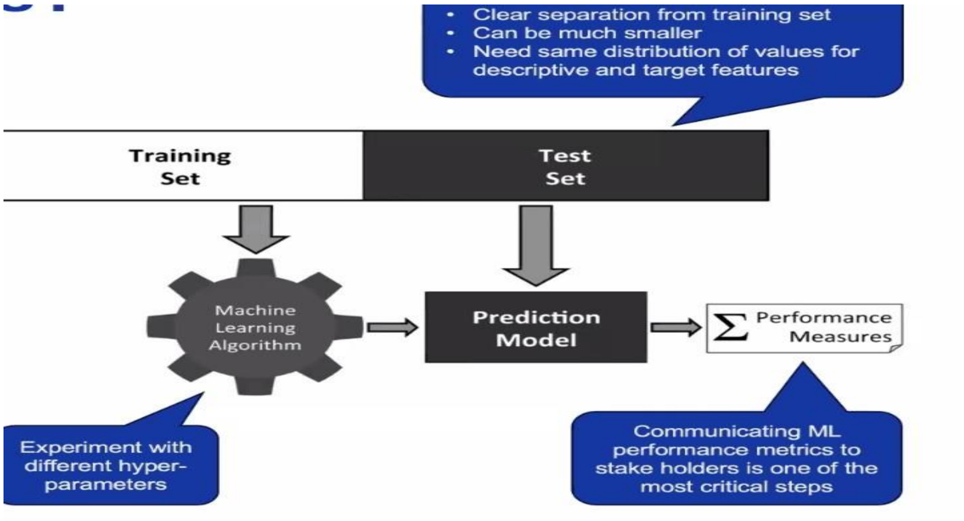
ML algorithms need a big data and data processing. Different steps are involved in preparing the data to be used for ML algorithms to make the predictions models as shown in following figures. ***(Shanthi et al., 2023)***

Figure (5) : Processing Data for use by ML models /Algorithms



Source: Forcier et al., 2019

Figure (6): machine Learning Algorithms for predictive models



Source: By the researcher

The most important part of construct an evaluation of predictive model or ML algorithms is ensuring that the data used to evaluate the model by separating the data to train and test data set to improve the accuracy of the performance. ***(Mrazek and O'Neill, 2020)***

The most popular ML classifiers algorithms are used in health sector, especially, the health financing domain are: Deep networks, Decision tree (DT) , Random Forest (RF) and Gradient boosting tress. The following table (4) summarizes the advantages and disadvantages of the above modeling that can be used for classification or regression problems. ***(Jyothsna, et al., 2022)***

Table (4): comparison between supervised models

Model	Advantages	Dis Advantages
Decision trees Model	It divides data into non-overlapping homogeneous groups. It is a simple method to implement but may not lead to high accuracy. Additionally, it can handle complex relationship between the target and predictors variables.	It may lead to overfitting.
Random Forest Model	Random Forest is an ensemble bagging technique that combines the aggregation and bootstrapping techniques of base trees to obtain final modeling of the results, and thus reducing overfitting. RF can provide higher accuracy for prediction performance and reduce variance.	It needs thousands of trained trees. The applicability gets more complicated.
Gradient Boosting Trees Model	It depends on boosting Techniques and sequential learning technique to control overfitting. Additionally, it has superior in accuracy of performance prediction over the previous techniques.	Each predictor is based on the results of previous prediction predictor.

Source: By the researcher

The health care data is a mix of structured, unstructured, and mix-structured data, therefore, if the data is fragmented, has no uniform digitalization practice, and disintegrated dataset, this leads to inaccurate results of Machine learning models.

AI applications have ability of feature generation from the following features such as: Health reports, social media, news, and media, which enables generating features from rapidly and complex data that support public health policy makers in decision-making.

Feature generation from complex data can be extracted easily from machine learning algorithms, especially, Deep Learning (DL). In other

words, artificial intelligence and Deep Learning have already been used for prediction epidemiology that enables appropriate optimization of the available resource. DL methods are commonly used respiratory disease studies. In addition to, using of DL has been increased during the COVID-19 pandemic. The COVID-19 pandemic initially caused some health care services to shift away from in-person transactions to a digital form, including Tele-health, E-mails, remote patient monitoring and other forms of communication. ***(Kolasa et al, 2024)***

2. Research objective

The aim of this research is to:

1. **Provide the assessment of the application of machine learning models for health financing, illustrating its potential effect on the health care financing and all UHC goals, and The Egyptian health system, which aims to achieve the equitable use of resources, efficiency, transparency, and accountability, alongside three final coverage goals: utilization according to need, financial protection, and quality of healthcare through the following :**
    - **Understanding the potentials of health digitalization and the effect of application ML and AI models in the health care system in Egypt when it comes to achieving UHC according to new Law in 2018.**
    - **Exploring the integration of public and private health care data within machine learning algorithms, using the big data, which consistent to the role of private insurance in Egyptian health system to accelerate UHC.**

2. **Assess the best-case studies of AI/ML applications in health care financing.**
3. **Propose the trends of regulation of ML applications within the health care system to achieve new UHC in Egypt.**
4. **Analyzing the approaches that lead to a decrease healthcare costs and health care spending by the affordability of health care.**

3. Research Importance

The importance of research is to assess the potentials of health digitalization in Egyptian health system in advancing UHC. This research is important for health care financing system in the Egypt and the private insurance companies in advancing Egypt's health reform agenda, through the following:

- **Insurance Fraud Detection and claims management: ML algorithms have been successfully deployed to detect fraud in health insurance claims, significantly reducing losses and ensuring more funds are available for patient care.**
- **Resource Optimization: Predictive models via ML applications help in optimizing staffing and resource allocation, improving service delivery and patient outcomes.**
- **Population Health Management: ML is used to manage population health by predicting chronic disease progression and optimizing preventive care interventions, thereby reducing overall healthcare costs.**
- **The integration of machine learning models in health financing for the UHC offers substantial benefits in terms of efficiency,**

cost-effectiveness, equity, and overall health system performance. These models enable a more responsive, data-driven approach to managing healthcare resources, ultimately supporting the goal of achieving UHC.

4. Research Methodology

The objective of this paper can be achieved through applying a qualitative approach using a literature review, which is an overview of the current Case Studies and Real-World Applications of AI and ML models for health financing objective, assessing its effect on advancing the UHC goal in Egypt.

This paper focuses on ML applications in health financing functions that have a significant affect accelerating UHC objectives as shown in this section.

Additionally, this study supports contribution of ML applications and how ML models that can be integrated into health care system to enhance health financing to achieve UHC goals

For the limitation of this literature review, it was carried out in PubMed, Scopus, and Web of Science from January 2000 to December 2023.

<u>This initial review is based on the following steps:</u>

(1) Identification: The titles, keywords, and abstracts of all identified publications were screened to independently evaluate their potential relevance.

(2) Full-text Screening: The full texts of all publications identified in the previous step were independently assessed for inclusion in the

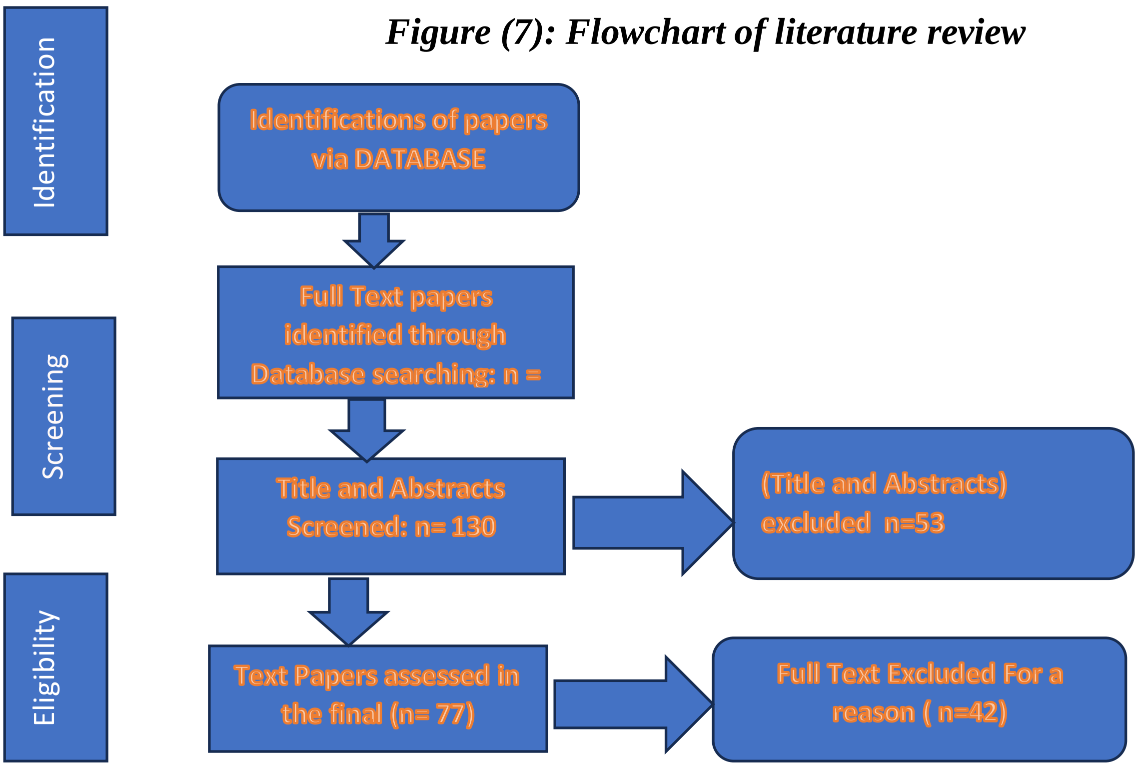
review and for data extraction, based on the inclusion/exclusion criteria and research objectives. The final decision for each paper was made after reviewing the title and abstract.

(3) Data charting: As depicted in Figure (7).

(4) Data extraction: Each study was reviewed for descriptive statistics, quality assessment and reporting methods were included, as shown in the appendix. This process was consistent with the following three categories: classification of data into groups or clusters, prediction, and analysis of structured data.

(5) Summarizing and reporting: The researchers recognized classifying the papers into a more detailed subtopic, mapping to health financing functions. Consequently, the literature review was grouped into five categories corresponding to different health financing domains, as shown in the following section.

Figure (7): Flowchart of literature review



Source: By the researcher

5. Implications and findings.

AI / ML achieve significant changes in health financing of the health care system. The systematic literature review and following studies have discussed various implications of AI and ML tools in the governance of health financing.

AI approaches can reduce inappropriate healthcare spending, progress toward interventions to reduce inappropriate healthcare utilization, and the optimal design of Benefit Packages based on definite criteria. Additionally, they have potential in identifying high-risk patients along with managing expenses and indirect costs, and implementing mitigation strategies, helps improve the efficiency and sustainability of the health system.

5.1 FORECASTING HEALTH EXPENDITURES

Implementation ML approaches to forecast high-cost patients is a hot topic for researchers; some papers discussed the development of ML models in forecasting of health expenditures using different types of ML algorithms.

Xie et al.(2015). This paper used one of supervised approaches, Bagging approach (Bagged regression trees) for modeling health costs in which data (i.e. clinical codes) are hierarchically structured to improve their prediction performance a patient's future days in hospital under Australia Voluntary health insurance data. This study revealed that different hierarchies of clinical codes do not lead to a significant effect on the performance predictive accuracy.

On the other hand, Yang et al. (2018) used another approach of ensemble approach (Gradient Boosting Machine (GBM), and

recurrent neural network) based on data of public health insurance in USA. To achieve the objective, this research compared the results from Supervised predictive models to predict expenditures, especially for "high-cost, high-need" patients, which are: "ordinary least square" (OLS) linear regression, Lest Absolute Shrinkage and Operator Regularized Regression, GBM, and using a deep learning approach (i.e recurrent neural networks). It summarized that the neural network demonstrates has the highest prediction accuracy among these models.

Kan et al. (2019) used different Regularized regression algorithms to predict future healthcare costs in older adults by using Medicare data from the USA. The findings of this paper illustrated that Regularized Regression model provides better performance of predictive power compared with OLS regression in predicting healthcare costs that leads to an increase in prediction performance, and may lead to enhance risk adjustment, and population health management in order to determine the health needs of targeted segments of population.

Nichol et al. (2021), this research conducts a review of mechanisms that use machine learning approaches according to predictive analytics in health-care settings. This study illustrated the "approaches" that predict utilization of health spending. Moreover, it improved efficiency by reducing cost of adverse effects on overall quality of healthcare.

Roger Muremy et al. (2020), the purpose of this study was to increase the prediction performance of the out-of-pocket (OOP) health expenditures in Rwanda by using machine learning algorithm techniques .To achieve this objective, the researchers used the Rwanda Integrated Living Conditions Surveys (EICV5) of 14580 households in 2018. The results can conclude that the machine learning approaches

were used to determine which predictor variable was important in our predictive model and comparison of the performance of the algorithms through train accuracy and test an accuracy metric measure that improves the accuracy performance. This paper recommended increasing significantly public spending on health. Additional, domestic financial resources are key to moving closer to (UHC). In addition, these results will be useful for assessing the OOP health expenditures dataset.

Finally, the study by Li Y-CJ et al.(2020), this paper aimed to assess the predictive power of laboratory tests, enhanced patient safety, and lowered unnecessary costs. The findings concluded that predicting accurately visit payments can identify patients requiring financial assistance. Additionally, this helps in creation of patient-focused payment plans, helping patients benefit from state-funded programs and manage network restrictions, OOP expenses, and the complexities of healthcare costs and billing systems.

From the above papers we can conclude that applications of AI and Machine learning can contribute to better prediction, more efficient spending, more equitable resource distribution and improved utilization, which lead to achieve the UHC.

5.2 RISK SCORING: RISK ADJUSTMENT VERSUS RISK SELECTION

Risk scoring can be defined as "the process by which information about an individual is used to predict uncertain assumptions". These assumptions may include: mortality rates, health care services

utilization, health care efficiency, and health care costs. Generally, Risk scoring approaches are based on mathematical function to link individual attributes, such as demographics and diagnoses, and predict the annual health care expenditures.

Many publications were contributed in ML applications based on data collected from compulsory and private health insurance can enhance risk adjustment or risk equalization models, which help in assuring efficiency and equitable allocation of resources across different pools.

Hileman & Steele (2016).This paper applied ML models to improve mechanism of the health risk adjustment among medical health insurance schemes , comparing an ensemble supervised models with the traditional regression risk-scoring models, training on Medical data, on its risk scoring performance for voluntary health insurance data. The ML approaches used features as diagnoses, pharmacy data and previous year cost for predicting relative risk. This study concluded that the ensemble learning machine may also have potential for commercial private insurance population.

Generally, many papers used the supervised learning models to enhance performance of risk adjustment models (health plan payment systems), as shown in McGuire et al. (2021). This study used Random Forest with Lasso penalized regression as shrinkage approach with application to compulsory private health insurance data in USA. This paper concluded the predictive model with shrinkage approach reduces costs, while a more uncertainty can be reinsured.

5.3 FRAUD DETECTION AND CLAIMS MANANGMENT

Using AI/ML approaches in health claim fraud has received a great attention from various academic researches such as health econometrics. The use of ML models can provide more accurate insights to inform health policy decisions. One of main advantages of ML algorithm approach is a reduction in administrative cost for the different health financing providers, particularly, in relation to claims management and fraud detection.

The health care fraud is the highest among all claim's insurance fraud in Egypt. Using hybrid supervised and unsupervised machine learning approaches have a potential in detecting claims frauds in an efficient and effective manner. Digital claims management has a potential for reducing the expenses for Egyptian health insurance system.

These studies uses data from voluntary health insurance as concluded in: Lu and Boritz (2005), Kirlidog and Asuk (2012), Gokturk and Kilic (2015) , Kumar Ghani and Mei (2010) ,and Ekin et al. (2013). However, many papers of modeling practices used public health insurance assessed supervised ML learning algorithms that classified claims of health insurance into legitimate and fraudulent claims as shown in Shin et al. (2012), this study proposed a scoring model that detects outpatient clinics according to information extracted from automated insurance claims.

Additionally, Sowah et al. (2019), this paper used public health insurance data in Ghana. This study used one of supervised methods that combine genetic algorithms with support vector machine learning

(GSVMs) to achieve the objective to overcome Oversampled problem health insurance claims data and reduce the health claims fraud. The conclusions of this study can be summarized as assessing three classifiers, and enhancing classification accuracy of fraudulent claims, additionally, reducing the computational time in order to process the claims.

5.4 DESIGN OF OPTIMAL BENEFIT PACKAGE

The following studies were discussed the design of the benefit package as follows:

Filho ,et al. (2021), this paper used NH survey data in Portugal. The aim of this paper was to describe segments within the uninsured population. To achieve this objective, K- means clustering method was used. The findings of this paper can be concluded as:

A. **There are three distinct groups of uninsured individuals: 1) young and middle-aged, healthy people with relatively high income and education levels ,2) older adults who suffer from chronic or long-term conditions; and 3) older adults with poor self-reported health.**
B. **Improving access to health care and priority of design benefit package were achieved from the results of the characteristics of the above groups.**

Kasy (2018), this study applied Gaussian process regression a one of Supervised ML algorithms to optimize policy decisions, such as tax or co-insurance rates in health insurance, assess the effect of the co-insurance rate on the health-care expenditures, and provide explicit formulas for posterior expected social welfare. Comparing to the results of the classical statistical models using the same data, achieving

an optimal reduction in the co-insurance rate concerning its impact on healthcare expenditure levels.

Matloob et al. (2021), the purpose of this paper was to set the priority of the design health benefit packages decision based on the records of individual employees health care, as opposed to the current practice of determining benefits on the basis of hierarchical position for employees. To achieve the objective, this research applied (unsupervised Learning Machine), Hierarchal clustering algorithms to historical medical records of the employees. Finally, the proposed approach achieved a 25% increase in the benefit package per employee.

5.5 ANALYSIS OF HEALTH COVERAGESCHEME

Assessing health utilization and health status based on the health coverage were discussed as shown in the following papers.

Chen et al. (2021), **this research examined the effects of Urban and Rural Resident Basic Medical Insurance (URRBMI) on the health of children in rural China, focusing on both preschool and school-age groups. Using supervised machine learning methods, the research concluded that URRBMI significantly enhances the health of preschool children, though it had no notable impact on school-age children. Additionally, this study illustrated the capability of causal forests to identify varying effects, providing valuable insights for policy-makers.**

Additionally, Kreif et al. (2020), this paper aimed to assess the effect of two different health insurance schemes in Indonesia (subsidized and contributory). The study concluded that significant variation in the benefits of contributory health insurance. However, no significant variation was achieved for the subsidized scheme, despite its concern

on vulnerable populations. Overall, offering potential information for policy design.

Finally, Cinaroglu (2020) and Niragire et al.(2020) concluded that the potential implication ML tools in analyzing High-Dimensional data that can help alleviation catastrophic health expenditures, and provide the needed budget. Additionally, traditional health insurance does not give protection for households from catastrophic (OOP) health expenditures. Inequality reduction requires utilization of a high dimensional- data approaches and strategies to effectively target poor households and empower the social and Health care system for them.

6. Conclusion and recommendation

The new Universal Health Insurance (UHI) Law in Egypt marks significant progress toward Universal Health Coverage (UHC), illustrating major changes in health financing functions. Recently, the focus has shifted to digital health systems, which incorporate artificial intelligence (AI), machine learning (ML) applications, and big data. This digital health system accelerates the achievement of UHC and achieves the sustainability of Egypt's health system. Policymakers are encouraged to integrate AI into their decision-making processes to enhance health financing outcomes.

In conclusion, this paper's findings can assist policymakers in improving resource allocation and optimizing health service delivery through targeted disease management programs for high-cost patients. The research adds to the literature by evaluating various AI/ML applications in the health financing domain, including revenue raising, pooling, and purchasing, ensuring that UHI effectively contributes to

UHC in Egypt. This study can serve as a basis for future research on AI/ML applications to explore complex relationships between health system components to improve health financing of Egyptian health system.

AI and ML applications can address healthcare system challenges related to health financing, such as inefficiencies, an aging population, chronic diseases, healthcare inequities, and sustainability. The paper identifies two main hot topics with potential: Forecasting the patients with high costs and health expenditure levels and, 2) health insurance claims management.

The applications of the ML /AI application in have potential affect to achieve the goal of UHC in the Egyptian health system and added value <u>for health financing through the flowing:</u>

1. **Exploring the forecasting of health expenditure levels for targeted individuals in order to improve the risk equalization.**
2. **Developing capitation-based payment models through Machine Learning-based risk adjustment.**
3. **ML models use for resource allocation monitoring by developing monitoring system for the primary healthcare network.**
4. **Automated Claim Management.**

Moreover, AI and ML applications can analyze complicated data sets that are challenging for humans to interpret and revolutionize health system financing, procedures, and policy-making. Although implementing AI/ML in healthcare systems presents challenges like ensuring patient privacy and upholding ethical principles, its advantages are well-documented. We urge policymakers to keep

investigating ways to integrate AI applications into their health decision-making processes to improve outcomes in health financing.

In conclusion, AI/ML applications are the potential for the healthcare system. However, there is a limited study of their impact on clinical practice,

This paper has many research limitations. First, ignoring the risks and ethical issues of AI/ML Applications in health financing. Second, this study doesn't investigate the potential of ML in other health functions and focused on the health financing Domain. Finally, it ignores Regulatory aspects and Ethical framework of AI applications in health care, which ensures data governance and data privacy.

According to the above conclusions which are discussed in detail above, the following recommendations can be stated:

1. **The AI/ML applications will make significant changes in financing healthcare in Egyptian Health system to achieve the progress toward UHC.**
2. **Effective governance and regulatory framework arrangements are critical to support AI and ML applications. This paper recommends applying digital claims management using ML Applications in order make the strategic health purchasing is more effective.**
3. **AI /ML Applications will support digitalization health in Egypt, which is developed by E-Health Company, a first of Health Company in Egypt, for the development, Management, and operation of health technology and digital Solution integration with e-finance.**
4. **The AI/ML applications depend on the quality and privacy of the data, this study recommends integration of public and**

private health care data with ML applications, with align with the role of private healthcare sector in accelerating new UHC law in Egypt. Additionally, it recommends the regulatory framework for ML and AI applications to mitigate data privacy of big data risks.

References

Abdelkader Dairi , Fouzi Harrou ,Ying Sun and Mohamed Mazen Hittawe. (2021). ***"Comparative study of machine learning methods for COVID-19 transmission forecastin". Journal of Biomedical Informatics.***

Ahmad Fasseeh, Baher ElEzbawy , Wessam Adly,Rawda ElShahawy,Amr ElShalakani ,and Zoltán Kaló. (2022). ***"Healthcare financing in Egypt: a systematic iterature review". Journal of the Egyptian Public Health Association*, https://doi.org/10.1186/s42506-021-00089-8.**

Ahmed Yehia Khalifa,Jean Yacoub Jabbour,Awad Mataria,Magdy Bakr, and Mai Farid (2021). ***"Purchasing health services under the Egypt's new Universal Health Insurance law: What are the mplications for universal health coverage?".International Journal Health Plann Management*, 37(2):619-631.**

Alami H, R. L. (2020). ***"Artificial intelligence in health care: laying the foundation for responsible". Glob health Journa,16*, 1-6**

Anzilli, L., & Giove, S. (2020). ***"Multi-criteria and medical diagnosis for application to health insurance systems: a general approach through non-additive measures"*. Decisions in Economics and Finance, 43(2), 559-582.**

Ashrafian H, Darzi A. (2018). "*Transforming health policy through machine learning". PLoS Medicine*, 15(11):e1002692.

Angelis A, Kanavos P, Montibeller G. (2017). "Resource allocation and priority setting in health care: a multi-criteria decision analysis problem of value? ".Global policy.

Altunay, S., Telatar, Z., Erogul, O., & Aydur, E. (2009). A new approach to urinary system dynamics problems: Evaluation and classification of uroflowmeter signals using artificial neural networks. Expert Systems with Applications, 36(3), 4891-4895.

Boccanera, F., & Brodsky, A. (2017). "OptiHealth: A Recommender Framework for Pareto Optimal Health Insurance Plans." In ICEIS (1) (pp. 599-609).

Chaparala Jyothsna,K. Srinivas , Bandi Bhargavi,Akuri Eswar Sravanth,Atmuri Trinadh Kumar, and J.N.V.R. Swarup Kumar. (2022). ***"Health Insurance Premium Prediction using XGboost Regressor"*. Proceedings of the International Conference on Applied Artificial Intelligence and Computing.**

Chen H, Xing J, Yang X, and Zhan K. (2021). "*Heterogeneous effects of health insurance on rural children's health in China: a causal machine learning approach"*. Int J Environ , 18(18):9616.

Choi, E. J., Choi, Y. J., Lee, S. W., Choi, Y. M., Ri, H. S., Park, J. Y., ... & Lee, Y. S. (2020). ***"Effect of anesthetic method on incidence of delirium after total hip replacement arthroplasty in South Korea: a population-based study using National Health Insurance claims data".*** **Korean journal of anesthesiology, 73(1), 36-43.**

Chu, B., & Qureshi, S. (2023).*"Comparing out-of-sample performance of machine learning methods to forecast US GDP growth"*.Computational Economics, 62(4), 1567-1609.

Cinaroglu. (2020). ***"Modelling unbalanced catastrophic health expenditure data by using machine-learning methods".. Intell Syst Account Finance Manag.,*** **27(4):168–81.**

Citlalli Blanchet, Alice Bluestone ,Craig Cartossa,Dolstad,and David Tuomala,. (2023). "*Digital Health After Covid Boom"*. Society of Actuaries Research and Institute Health Care Cost Trends.

Dumpala Shanthi, Madhuravani ,& Ashwani Kumar. (2023). ***"Handbook of Artificial Intelligenc".*** **Singapore: Bentham Science Publishers Pte. Ltd. .**

Ekina T, Ieva F, Ruggeri F, and Soyer R. (2018). ***"Application of Bayesian methods in detection of healthcare fraud". Chem Eng Trans,*** **33:81–9.**

García-Centeno M-C, Mínguez-Salido R, del Pozo-Rubio R. (2021). ***"The classification of profiles of financial catastrophe caused by out-of-pocket payments: amethodological approach". Mathematics (Basel),*** **9(11):1170.**

Geoffrey R. Hileman,Syed Muzayan Mehmud, and Marjorie A. Rosenberg. (2016).*" Risk Scoring in Health Insurance:A prime"*. Society of Actuaries.

GlobeMed Egypt. (2023)."*Harnessing the Role of the Private Sector in Advancing univsesal Health Coverage Agenda in Egypt"*. NorthEastern Universiy.

Gupta S and Tripathi P. (2016). ***"An emerging trend of big data analytics with health insurance in india".*** **I*nernational Conference Innov. Challenges Cyber Securiety, (pp. 64-69).***

Hassan AKI, Abraham A. (2013)."Computational intelligence models for insurance fraud detection: a review of a decade of research". Journal of Network Computer Applied.

Hetta, R. (2024)."*Implementing Universal Health Insurance: Case Study of Stakeholders' Perspectiv erspectives in in Port Said, Egypt"*. Master Thesis, American University in Cairo.

Inke Mathauera and & Maarten Oranje. (2023). "*Machine learning in health financing: benefits, risks and regulatory needs". Bulletin of the World Health Organization*.

Jiang S, Chin KS, Tsui KL. (2018). *"A universal deep learning approach for modeling the flow of patients under different severities". Computional Methods Programs Biomed*, 154:191-203.

Santosh, K. C., & Gaur, L. (2022). *"Artificial intelligence and machine learning in public healthcare: Opportunities and societal impact"*. Springer Nature.

Katarzyna Kolasa, Bisrat Admassu, Malwina Hołownia-Voloskova, Katarzyna,Jean-Etienne Poirrier & Stefano Perni. (2024). *"Systematic reviews of machine learning in healthcare: a literature review". Expert Review of Pharmacoeconomics & Outcomes Research* ., VOL. 24, NO. 1, 63–115.

Kirlidog M, Asuk C. (2012). *"A fraud detection approach with data mining in health nsurance". Procedia Society Behavior Science*, 62:989–94.

Koutsojannis C, Nabil E, Tsimara M, et al. (2009). "Using machine learning techniques to improve the behaviour of a medical decision support system for prostate diseases". Ninth International Conference on Intelligent Systems Design and Applications (pp. 341-346). IEEE.

Kriegeskorte N, Golan T. (2019). "*Neural network models and deep learning". Current Biology.* , 29(7):R231–6.

Kwadwo Arhin , Eric Fosu Oteng-Abayie and Jacob Novignon. (2023). *"Assessing the efciency of health systems in achieving the universal health coverage goal:evidence from Sub-Saharan Africa". Health Economics Review*, 13-25.

Li, L., Bagheri, S., Goote, H., Hasan, A., & Hazard, G. (2013).*"Risk adjustment of patient expenditures: A big data analytics approach"*. IEEE Iternaional Confrence of Big Data (pp. ISBN:978-1-4799-1293-3).

Liu X, Fang C, Wu C, Yu J, Zhao Q. (2021). *"DRG grouping by machine learning: from expert-oriented to data-based method"*. BMC Med Inform Decision Making. , 21(1):312.

Lu F, Boritz JE. (2005). *"Detecting fraud in health insurance data: learning to model incomplete Benford's Law distributions"*.16th European Conference on Machine Learning,, (pp. 33–40), Portuga.

1. Ma, M. (2022). *"Research on the Development of Hospital Intelligent Finance Based on Artificial Intelligence"*. Computational Intelligence and Neuroscience.

Manning WG, Basu A, Mullahy J. (2005)."Generalized modeling approaches to risk adjustment of skewed outcomes data". Journal of Health Economics.

Mathauer, I., Dale, E., Jowett, M., & Kutzin, J. (2019). "Purchasing health services for universal health coverage: how to make it more strategic"? HEALTH FINANCING POLICY BRIEF NO. 6.WHO

Matloob I, Khan SA, Hussain F, Butt WH, Rukaiya R, Khalique F . (2021). *"Need-based and optimized health insurance package using clustering algorithm"*. Applied Science, 11(18):8478.

Mélanie Bourassa Forcier, Hortense Gallois, Siobhan Mullan and Yann Joly. (2019). *"Integrating artificial intelligence into health care through data access: can the GDPR act as a beacon for policymakers?"*. Journal of Law and the Biosciences, 317–335.

Monique Mrazek and Felicity O'Neill. (2020). *"Artificial Intelligence and Healthcare in Emerging Markets"*. Public Disclosure Authorized.

Muremyi R, Haughton D, Kabano I, Niragire F. (2020). *"Prediction of out-of-pocket health expenditures in Rwanda using machine learning techniques"*. Africian Medicine Journal, 37:357.

Musulin J, Baressi Šegota S, Štifanić D, et al. (2021). *"Application of Artificial intelligence-based regression methods in the problem of COVID-19 spread prediction: a systematic review"*. International Journal *Environ Res Public Health.*

National Health Authoriety . (2023). *"Global Review of the role of Artificial Intelligence and Machine Learning in HEalth Care Financing for UHC"* . India: World Health Organization.

Ng SHX, Rahman N, Ang IYH, Sridharan S, Ramachandran S, and Wang DD. (2020). "*Characterising and predicting persistent high-cost utilisers in healthcare: a retrospective cohort study in Singapore"*. *BMJ open*.

Nichol AA, Batten JN, Halley MC, Axelrod JK, Sankar PL, Cho MK. (2021)." *A technology of existing machine learning-based predictive analytic tools focused on reducing costs and improving quality in health care: systematic search and content analysis"*. Journal of Medicine Internet Research, 23(6):e26391.

Nomura Y, Ishii Y, Chiba Y, Suzuki S, Suzuki A, Suzuki S et al. (2021). *"Does last year's cost predict the present cost? An application of*

machine leaning for the Japanese Area-Basis Public Health Insurance Database". **International Journal Environ Res Public Health, 18(2):565.**

Ortega P, Figueroa C, Ruz G. (2006). ***"A medical claim fraud/abuse detection system based on data mining: a case study in Chile".*** **Springer Journal.**

Poly, T. N., Islam, M. M., Li, Y. C., Lin, M. C., Hsu, M. H., & Wang, Y. C. (2021). ***"Metformin use is associated with decreased mortality in COVID-19 patients with diabetes: evidence from retrospective studies and biological mechanism".*** **Journal of clinical medicine, 10(16), 3507.**

Ramezani, M., Takian, A., Bakhtiari, A., Rabiee, H. R., Fazaeli, A. A., & Sazgarnejad, S. (2023). ***"The application of artificial intelligence in health financing: a scoping review".*** **Cost Effectiveness and Resource Allocation, 21(1), 83.**

Roger Muremyi, Dominique Haughton, Ignace Kabano, François Niragire. (2020). ***"Prediction of out-of-pocket health expenditures in Rwanda using machine learning techniques".*** **Pan African Medical Journal, 37(357).**

Roger Muremyi,Dominique Haughton, Ignace Kabano, François Niragire.(2020). ***"Prediction of out-of-pocket health expenditures in Rwanda using machine learning techniques".*** **Pan African Medical Journal, 37(357).**

Rose, S. (2016)."A machine learning framework for plan payment risk adjustment". Health services research, 51(6):2358–74.

Rose, S. (2020). ***"Modelling unbalanced catastrophic health expenditure data by using machine-learning method*". Intelligent Systems in Accounting, Finance and Management, ;27(4):168–81.**

Santosh, K. C., & Gaur, L. (2022). ***"Artificial intelligence and machine learning in public healthcare: Opportunities and societal impact".*** **Springer Nature.**

S, G. (2008). ***"The essential nature of healthcare databases in critical care medicine".*** **Vol.12(5): 176. Doi: 10.1186/cc6993.**

S, R. (2018). ***"Robust machine learning variable importance analyses of medical conditions for health care spending*". Health services research.**

Surya K. ,Kapeleshh S ,Erik ,Mitja Luštrek ,Barbara G. ,Kathiravan S.n ,Yu-Chuan Li ,Anton G. (2021). "*Machine Learning Prediction Models for Chronic Kidney Disease Using National Health Insurance Claim Data in Taiwan". MDPI.*

The World Bank. (2020).*"SUPPORTING EGYPT'S UNIVERSAL HEALTH INSURANCE SYSTEM PROJECT." Health, Nutrition, and Population Global Practice,Middle East and North Africa Region.*

Troy JD, Torrie RM, & Warner DN. (2021). *"A machine learning approach for identifying predictors of success in a medicaid-funded, community-based behavioral health program using the child and adolescent needs and strengths" . Child and Youth Service Review.*

Yamashita, K., Yoshiura, T., Arimura, H., Mihara, F., Noguchi, T., Hiwatashi, A. & Honda, H. (2008). *"Performance evaluation of radiologists with artificial neural network for differential diagnosis of intra-axial cerebral tumors on MR images".* American journal of neuroradiology, 29(6), 1153-1158.

Wang S. (2019). *"Data integration of electronic medical record under administrative decentralization of medical insurance and healthcare in China: a case study"*. Health Policy Research.

WHO. (2021).*" Digital technologies for health financing: what are the benefits and risks for UHC? Some initial reflections". Health Financing Working Paper 19,. Switzerland: World Health Organization.*

WHO. (2023). *"The role of digital claims management for Estonia's health insurance: a leverage for making healthcare purchasing"* . Geneva,World Health Organization.

WHYTE T, OMOYIOLA, Bayo O. (2023). *"INTEGRATION OF PUBLIC AND PRIVATE HEALTH CARE DATA WITH MACHIE LEARNING".*

WHO. (2023). "*The implications of artificial intelligence and machine learning in health financing for achieving universal health "*. World Health Organization.

World Population Review [Internet].2020. "Egypt Population 2020 (Demographics,Maps, Graphs)". https://worldpopulationreview.com/countries/egyptpopulation . Accessed 5 May 2020.

APPENDIX: Quality Assessment of systematic literature review

Author (Year)	Is the study population clearly described?	Are competing alternatives clearly described?	///Is a well-defined research question posed in answerable form?	Is the economic study design appropriate to the stated objective?	Is the chosen time horizon appropriate in order to include relevant costs and consequences?	Is the actual perspective chosen appropriate?	Are all important and relevant costs for each alternative identified?	Are all costs measured appropriately in physical units?	Are costs valued appropriately?	Are all important and relevant outcomes for each alternative identified?	Are all outcomes measured appropriately?	Are outcomes valued appropriately?	Is an incremental analysis of costs and outcomes of alternatives performed?	Are all future costs and outcomes discounted appropriately?	Are all important variables, whose values are uncertain, appropriately subjected to sensitivity analysis?	Do the conclusions follow from the data reported?	Does the study discuss the generalizability of the results to other settings and patient/client groups?	Does articl indic that t is no poten confl of intere of stu resea r(s) a funde ?
Adab 2018	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Aguilar 2015	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	N	Y	N	Y
Ahern 2018	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Anderson 2014	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y
Beckman 2015	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Blakely 2014	Y	Y 47+646	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Breheny 2020	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N	Y
Brown3rd 2013	Y	N	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	N
cinaroglu 2020	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N
Davis et al. 2021	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	Y
chen et al. 2021	Y	Y	Y	Y	Unclear	Y	Y	Y	Y	Y	Unclear	Unclear	Y	N	Y	Y	Y	Y
Conner 2019	Y	Y	Y	N	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	N
Sowah et al. (2019)	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dino 2008	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	N
Ekwaru 2017	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ekwaru 2020	Y	Y	Y	Y	Y	N	Unclear	Y	Y	Y	Y	Y	Y	N	Y	Y	N	Y
Ekwaru 2021	Y	N	Y	Y	Y	Y	Unclear	Y	Y	Y	Y	Y	Y	N	Y	Y	N	Y
Dos Santos, Dias & Filho (2021)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Garmy 2019	Y	Y	Y	N	N	N	N	N	N	N	Y	Y	Y	N	N	Y	Y	N
Kose, Gokturk & Kilic 2015	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Hileman & Steele 2016	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Jadambaa 2022	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Kesztyüs 2013	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N
Matloob et al. (2021)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N

Lee 2017	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Legood 2021	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Li 2019	Y	Y	Y	Y	N	Y	N	N	N	Y	Y	Y	Y	N	N	Y	Y	N
Guire, Zink & Rose 2020	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	N
Mihalopoulos 2012	Y	Y	Y	N	Y	Y	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	N
Nichol et al.2020	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
kan et al. (2019)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Philipsson 2013	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Phua 2021	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ross 2018	Y	Y	Y	Y	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rush 2014	Y	N	Y	N	Y	Y	N	Y	Y	N	Y	Y	Y	Y	Y	Y	N	N
Simon 2013	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Kasy 2020	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Kreif et al. (2020)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N
Sutherland 2016	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N	Y
Tengs 2001	Y	N	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	N	N
joedicke et al. (2019)	N	N	Y	Y	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	Y	N	Y
Võrno 2017	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N
Wang 2001	Y	N	Y	Y	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	Y	N	N
Wang 2003	Y	N	Y	Y	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	Y	Y	N
Wang 2008	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	N	Y	Y	N	N
Willems 2021	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Xie 2015	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Zandieh 2021	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y
Zandieh 2022	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N	Y
Zaleski 2021	Y	N	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N