प्रधानमंत्री जन आरोग्य योजना
आयुष्मान भारत
PM-JAY

सत्यमेव जयते
national health authority

World Health Organization
India

Global review of the role of artificial intelligence and machine learning in health-care financing for UHC

Policy Brief

Global review of the role of artificial intelligence and machine learning in health-care financing for UHC

August 2023

Policy brief: Global review of the role of artificial intelligence and machine learning in health-care financing for UHC

ISBN: 978-92-9021-060-3

Suggested citation. Policy brief: Global review of the role of artificial intelligence and machine learning in health-care financing for UHC. New Delhi: World Health Organization, Country Office for India; 2023. Licence: CC BY-NC-SA 3.0 IGO.

Cataloguing-in-Publication (CIP) data. CIP data are available at http://apps.who.int/iris.

Printed in India

Acknowledgement

This report is a ‘Global review of the role of artificial intelligence and machine learning in health-care financing for UHC’. It highlights current & emerging application of AI-ML in the field of healthcare financing, especially as they relate to the core health financing functions.

The WHO study team would like to acknowledge Oxford Policy Management Ltd. For their contribution in execution of the study. Valuable input and comments were received from Inke Mathauer (WHO Geneva). The study team is also grateful to officials at the National Health Authority (NHA) and global experts and practitioners working in the area of AI-ML for health financing.

Project Team

World Health Organization
Dr Grace Achungura
Mr Jaidev Singh Anand
Dr Hilde De Graeve

Oxford Policy Management Ltd.
Ms Louise Allen
Mr Paul Jasper
Dr Arpita Chakraborty
Ms Agrima Sahore
Ms Poorva Shekher
Ms Kirti Gupta

National Health Authority
Dr Basant Garg
Mr Kiran Gopal
Mr Vikram Pagaria
Mr Akshay Jain

1. Background

The aim of Universal Health Coverage (UHC) is to ensure that people have access to health care as per their need, without having to suffer financial hardship (World Bank, 2022). Sustainable Development Goal 3.8 also highlights that the target is to "*achieve universal health coverage, including financial risk protection, access to quality essential health care services, and access to safe, effective, quality, and affordable essential medicines and vaccines for all*" (UNDP, 2015). Experts suggest health insurance can be one of the key support processes to achieve UHC. It can help in mitigating high secondary and tertiary care expenses for people, particularly the poor and vulnerable segments of society (Planning Commission, 2011).

In support of achieving UHC, the Government of India (GoI) launched the government-sponsored health insurance scheme called "Pradhan Mantri Jan Arogya Yojana" (PMJAY) in 2018. The PMJAY aims to bring more than 107 million of the most vulnerable families in the country under the ambit of health insurance, to provide tertiary and secondary level care. Together with PMJAY, the launch of the Ayushman Bharat Digital Mission (ABDM) in 2021 set the overall objective to leverage a platform of information technology (IT) to support the existing health systems in a "citizen-centric" approach.

This set the stage to explore and utilize the latest in IT and computational technology for health, aimed at building a robust health system to provide quality care to all citizens. Against this backdrop, this global review focused on understanding the potential applications of Artificial Intelligence (AI) and Machine Learning (ML) in health-care financing (particularly in health insurance), with a focus on publicly funded health systems.

The study's overall objective was to assess the benefits and challenges of AI and ML for the effective functioning of such systems, in tandem with India's PMJAY scheme. The review aimed to answer the following for health insurance (HI): (i) what are the types of AI/ML applications prevalent in the HI industry?; (ii) what are the uses and related impacts of AI/ML in HI?; (iii) what are some best practices/case studies of AI/ML in HI?; (iv) what is needed in the institutionalization of AI/ML in health care financing, and its related potential pitfalls and enabling factors?

This review focused on the potential of AI/ML applications to support operational efficiency in using limited resources to the best effect and did not consider AI/ML applications pertaining to health-care delivery, nor to diagnostics in particular. The focus remained on the application of AI and ML algorithms (that is, software) to data in health-care financing.

2. Approach and methodology

The administration of health insurance is a complex process with high transaction volumes and substantial amounts of complex clinical, financial, and administrative data. The core value-adding processes of a publicly funded HI scheme generally include the following: (1) develop, maintain and price benefit packages; (2) establish and maintain provider and hospital networks; (3) eligibility review and beneficiary enrolment; (4) maintain beneficiary membership database; (5) link beneficiary with facility/provider; (6) pre-authorise treatment; (7) receive and adjudicate claims, update beneficiary database; (8) pay provider or refund member; (9) reconcile claims, risk equalisation and forecast expenditure; and (10) provide beneficiary customer care. The support processes which run across these functional areas include finance and risk management, information systems, human resources, and governance.

These processes were further carefully categorised into broad functional categories, namely *(a) Benefit design and pricing; (b) Beneficiary management; (c) Claims management; (d) Provider selection and payment and (e) Fraud management,* which facilitated the careful synthesis of evidence. This framework guided us in assessing AI/ML applications to health-care financing. It also aided the narrative of the literature review for this study to ensure that no key developments were missed in this area.

This study used a snowball approach and deployed two parallel arms of research- one primary information, which comprised qualitative research via expert interviews undertaken during its course; and the other secondary, which included a detailed round of desk research and literature review based on the conceptual framework. Key informants were identified based on their familiarity with the research topics and who operated in the confluence of technology and health-care financing. A total of eleven expert interviews were conducted, using a semi-structured interview guide. For the literature review, an indicative list of keywords, developed based on the conceptual framework, was used to conduct the desk search. The literature review included both published, peer-reviewed literature and grey literature. Literature published from 2009 was included, and the geographic focus included both developed and developing countries. A total of 185 documents were reviewed by the researchers in this study.

3. Findings

Consolidated evidence across study components, that is, secondary research and expert interviews, is presented below for each of the functional categories identified from the conceptual framework. For each category, we briefly discuss what they comprise, how the use of AI/ML can be beneficial to public health insurance, the overall key findings and the scope for the future.

3.1 Benefit design and pricing

Developing, maintaining, and pricing benefit packages is a key step in publicly funded health insurance schemes. Areas in which ML can assist with the same were explored and identified as follows, a) analyse a large number of input factors and rank them in order of relevance; b) assist in identifying factors that affect the premium cost and c) in underwriting and cost prediction. However, most use cases regarding this have been witnessed in the private sector so far since the cost of the premium is an important factor to consider for increasing the uptake of insurance amongst everyday people. (Mladenovic et al., 2020; Rawat et al., 2021). In the public sector, it can potentially assist the government to predict the cost and plan the budget as per the need of the population.

Feature selection techniques have been used to identify “meaningful and decisive factors” for claim filing and acceptance in the USA. It has been found that continuous variables (for example, age, BMI) are more important than categorical variables for claim analysis (Rawat et al. (2021)). Predicting the most viable input factors can potentially assist in ranking the wide range of input factors and highlight the ones for which data needs to be collected accurately (Wang, 2021). This can help the government to systematically collect panel data for the most relevant factor which can potentially help in more acute cost estimation. In the case of the PMJAY scheme in India, ML can be used in this area by states which have opted for the insurance-based or hybrid model. ML-powered input can help them with a more accurate estimation of the premium paid for each beneficiary. The government can also avoid the disconnect between aspirational health plans and available financial resources, and accordingly choose health benefits packages.

In private health insurance, the use of ML algorithms has also been observed in reducing underwriting time by analysing past data to derive rules or categories for future claims analysis. Pure underwriting might not be required in public health insurance as it does not exclude people based on risk level. However, in case of the PMJAY scheme, it is still necessary for state governments to understand the risk level of the population and quantify the risk. This can help the government to apply risk- equalisation techniques so that the medical expenses of higher-risk individuals are shared among health-care or insurance providers. This can aid with deciding premiums for states which have opted for insurance-based or hybrid model under PMJAY. Studies by Hanafy and Ming (2022) and Wang (2021) showcase how ML models or methods can be used in underwriting and in classifying customers' basis risk categories, which can also help with the way premiums are set. As the Indian government currently rolls out the Diagnosis Related Groupings pilot[1] to account for comorbidities, the PMJAY scheme could benefit from using ML models which can potentially create patient classification based on different factors like demographic, diagnostic and therapeutic attributes that can help determine the level of resource intensity for each group.

3.2 Beneficiary management

Beneficiary management in health insurance includes beneficiary identification, enrolment and maintenance of the beneficiary database, helping improve cost efficiency and customer satisfaction (Asian Development Bank, 2021). Customer care targeted at beneficiaries is also an essential part of delivering quality services. This section covered the following components from the conceptual framework: a) eligibility review and enrolment; b) maintain beneficiary membership database; and c) provide beneficiary customer care.

Use of AI/ML in beneficiary identification has been very limited, and its application has not been seen in the health-care sector so far. Some use has been explored in improving the targeting of aid for poor populations in poor geographies, by searching and identifying people in need. One such example is the use of deep learning pipeline and ML algorithms by the Government of Togo to enable granular geographic targeting for their social assistance program (Novissi), wherein the aim was to identify the poorest one hundred cantons in the country to directly identify and prioritize the country's poorest people (Blumenstock, 2021).

Application of AI/ML technologies in beneficiary enrolment has been very limited, and not explored yet in the health-care sector. Social protection is one area in which the use of AI/ML has been explored, wherein a comparison of a beneficiary's profile with the scheme or programme eligibility criteria allows eligibility decisions to be made, turning eligibility and benefit level decisions into ML tasks (Ohlenburg, 2020). One possible application is an update in personal characteristics initiating a data-driven re-assessment, making a given scheme

[1] Under PMJAY, there was pilot launch of Diagnosis Related Grouping (DRG) in 5 states of Chhattisgarh, Haryana, Kerala, Maharashtra, and Meghalaya. AB PM-JAY will be the first insurance scheme in the India to provider payment mechanism through DRG.

or programme more responsive to changes in circumstances, so that the enrolment of beneficiaries can be efficient and up-to-date (Ohlenburg, 2020).

Some interesting uses of AI/ML technology has been found in beneficiary authentication. Key examples of this include “liveness checks”, “demographic comparison” and “identity authentication” which are AI/ML based solutions being adopted by countries like India and Philippines (Kurmanath, 2019); (PhilHealth, 2019). These aim to reduce and eventually eliminate the need to physically authenticate people and use information accumulated in public data systems to check beneficiary details provided by them. This assists in maintaining updated beneficiary databases and in validating if an existing beneficiary is indeed still alive or may have died.

Beneficiary databases created by integrating unique beneficiary identification mechanisms within health insurance programs can improve effectiveness and efficiency in increasing coverage. These databases can be used by both health-care providers and insurers, to ensure all eligible people can be served well, and nobody is left out. Such a database will also enable the use of ML technologies, by offering large quantities of data that is complete, representative, and up to date. For countries that witness continuous domestic migration due to the presence of seasonal workers or have a significant part of their population employed in the informal sector, such as India, maintaining accessible and efficient beneficiary databases will be important in offering greater coverage and efficiency of their public health schemes.

Customer care targeted at beneficiaries is also an essential part of delivering quality services. Developments in ML technologies, especially around natural-language processing (NLP), have enabled the use of chatbots for automation of customer service tasks with significant efficiency gains. One key example in this area is automated chatbots that provide convenient access to data leveraged through a discussion-like interface. A study by Riikkinen et al. (2018) was among the first to systematically identify and assess chatbots currently being used by insurance actors in the market. It discussed how ML technology and chatbots could be used to create value in insurance for customers by functioning at the intersection of theoretical (that is, service logic and reverse use of customer data), technological (that is, AI) perspectives along with industry phenomenon (that is, efficient transfer of resources and processes using digitalization).

In the case of public health insurance, where a wide variety of beneficiaries have to be served, beneficiary customer care can become an expensive and exhaustive component. The use of ML technologies can therefore aid in delivering informative content available on websites, like in the case of the PMJAY portal, but also offer highly personalized solutions to customers’ problems by harnessing vast amounts of customer data. (Riikkinen et al. (2018)). The Central Grievance Redressal and Management System, established to redress PMJAY related grievances can also explore the use of chatbots for beneficiary customer care to provide swift and timely attention to smaller concerns compared to the current set-up of registering a grievance and then tracking it on the system.

3.3 Claims processing

This section explored the use of AI/ML for pre-authorisation and claim adjudication, as also stated in the conceptual framework. Claim processing refers to the procedure of reviewing claims and auditing them, and then deciding what the next processing steps are to be. A study based in Germany highlighted that although as many as 70% of claims are flagged as doubtful, only 10% of those cases are objected (Hehner, 2017). As per an assessment of PMJAY in 6 states, claim rejection rates are 2.3% in states that opted for the insurance model and 4.8% in states which opted for the trust model. It is higher for states like J&K (6.4%), Himachal Pradesh (5.5%), and Uttar Pradesh (5.5%) between 2019-21 (WHO, 2022). Many of the claims are also rejected because of errors in the forms like coding and billing errors (Johnson et al., 2021). Given that traditionally audits are implemented by humans, they not only take significant time, manpower and money but also cause hassle to patients under care. There also remains a chance of error where incorrect claims are paid. AI/ML can provide a solution to prevent claim denials and reduce the processing time for preauthorization.

AI/ML process for faster claim resolution

Historical transaction and past data analysis: This can help in deducting any unusual request or duplicate/similar transactions as well as faster identification of legit claims.

Text data processing: AI/ML can potentially go through a large amount of free text data in the claim form through data scrapping technologies and remove any noise from the information.

Image data processing: Image data from various scans, reports or pictures can be converted into pre-learned concepts or labels by using computer vision models.

One of the KII respondents from India also emphasised the need of implementing AI-based processes which can identify the type and accuracy of documents before they are added to the insurance portal for claim settlement. This can help in reducing the number of ineligible documents, minimise tagging documents in the wrong column and reduce the number of queries sent back to the providers. AI/ML can help in these processes by using natural language processing systems (Wang, 2021). The PMJAY scheme in India has also established digital measures for claim settlement which is a pre-requisite for applying any AI/ML-based processes. However, a mixed methods study conducted in Uttar Pradesh and Jharkhand showed that some of the claim management processes are manual and a large number of queries are raised by the insurance agencies, which increases the processing time (Furtado et al., 2022).

Another noticeable challenge in claim processing also includes the pre-authorization process . Many studies based in the USA have shown that delays due to pre-authorization have resulted in increased emergency department visits (Choudhury and Perumalla, 2021; Hartung et al., 2004) poor adherence (Choudhury and Perumalla, 2021; Happe et al., 2014) and increased medical expenses (Choudhury and Perumalla, 2021; Margolis et al., 2009). A recent study based in India also highlighted that late initiation and lack of documentation are the primary reason for the rejection of pre-authorization requests (WHO, 2022). A study by Choudhury and Perumalla (2021) also showcased how an ML model called CHAID (Chi-squared automatic interaction detector) algorithm could aid with pre-authorization for post-acute care/post-hospitalization, reducing delays caused due to pre-authorization by 22%.

[2] Pre-authorization is a process which requires healthcare providers or beneficiaries to obtain advance approval for a claim from the insurer before any specific service is delivered to the patient to qualify for payment coverage.

3.4 Provider selection and payment

Purchasing comprises the allocation of pooled funds to health-care providers for the delivery of health-care services. It is considered strategic when these allocations are associated with information on provider performance and the health needs of the population being served; with an aim to increase equitable distribution of resources, manage expenditure growth and achieve efficiency gains (WHO, 2021).

In the case of a public health insurance scheme in India, the government can choose from a mix of both public and private health-care providers and insurers. This means large quantities of data exist across these stakeholders, which carries the potential for added value, but which is seldom harnessed (Allal-Chérif et al., 2021). However, an in-depth analytical assessment of these large datasets can aid the purchasing function in several ways by enabling the use of varied AI/ML technologies. More efficient and transparent use of this data can be made possible when AI/ML models or algorithms are processing and understanding data, to draw relevant inferences (for example, performance history of insurance providers, premium prices offered across different insurance providers) for buyers, in place of humans having to work through the same.

Our findings demonstrate that the use of AI/ML technologies has been explored by the private sector in their purchasing departments in many different ways. For example, supplier selection using matching systems in the private sector assist buyers to select a supplier from a large pool by recommending the best procurement sources for specific needs using a semantic analysis tool and ML technologies, like in the case of Silex (SaaS cognitive sourcing platform). Predictive analysis technologies have also been used in the private sector (for example, by SAP Ariba) to develop knowledge for buyers on internal and external clients, and their partnerships using multidimensional data and algorithms. Combining AI and ML technologies to build purchasing strategies based on cost analysis and cost prediction are also used in the private sector (for example, Direct SRM, Total Supplier Manager) to improve cost management and build helpful supplier relationships through performance monitoring and managing risks.

In the case of public health insurance, although the use of AI/ML technologies has not been witnessed, the examples shared above are indicative of possibilities which exist for governments to explore. The government can carefully determine efficient providers using relevant indicators such as ALOS, time to claims upload, etc. by using ML technologies and relevant datasets. Incentives and penalties (if needed) can also be explored by governments for providers basis better understanding of their performance. This can help enable better allocation of resources between empanelled hospitals, and to maintain a strong provider database by eliminating any faulty or poor-performing providers. They could also be used to identify empanelled hospitals more in need of resources than another for a given geographic spread and health risk burdens to ensure the right population can be provided quality health-care services. In the case of public health insurance where the government has to reimburse insurance providers (public and private both), possible applications can be explored from the private sector, such as automating workflows to facilitate straight-through processing of payments using AI and applying image recognition to documents (Barclays, 2019).

3.5 Fraud management

Fraud management is a cross-cutting support process that runs across different functional areas as stated in the conceptual framework. This section explored different AI/ML techniques that have been used in detecting frauds in an efficient manner and innovations that hold potential for further exploration and scale-up.

In India, health-care fraud is of significant concern with the health-care industry overall losing approximately Rs 600-800 crores in fraudulent claims annually (Rawte and Anuradha, 2015). In Ghana, the National Health Insurance Scheme is faced with threats to its financial sustainability as a result of fraud (Amponsah et al., 2022). These fraud and corrupt practices found within the claims processing lifecycle have contributed to challenges for the citizens and residents of the country to benefit from Universal Health Coverage (UHC). Contrary to popular belief, insurance fraud is not a victimless crime as the cost of the crime is passed onto law-abiding citizens in the form of increased premiums or serious harm or danger to beneficiaries (Kruse et al., 2016). To combat this kind of societal threat, there is a need for health-care fraud detection systems to evolve.

Some use case examples

- Amponsah et al. (2022) proposed a novel method wherein a combination of blockchain technology and machine learning algorithm was used to detect and prevent fraud in health insurance claims using Ghana's National Health Insurance Scheme (NHIS) data. Machine learning was leveraged to equip the blockchain smart contract.[2] This study concluded that the proposed system enhanced the blockchain smart contract's ability to detect fraud with an accuracy of 97.96%.
- Bauder et al. (2018) conducted an empirical study of various unsupervised machine learning methods to detect outliers and indicate fraudulent medical providers, with the backdrop of the US Medicare program and related fraudulent cases involved. Findings from this study suggested that using ML techniques helped reduce the time and number of resources needed to identify fraud, by narrowing down the providers that required additional investigation.

AI/ML methods can use data from various sources like electronic medical records (EMRs), devices, pharmacy claims and lab reports to help in the classification, clustering, outlier detection and identification of legitimate and fraudulent cases based on patterns in the data (Hassan and Abraham, 2013). AI/ML techniques have also been used to help reduce the time and number of resources needed to identify fraud, by narrowing down the providers that require additional investigation (Bauder et al. (2018)). Although unsupervised AI/ML techniques are regarded to hold promise in detecting fraudulent providers, work is needed in improving specificity and avoiding too many false positives.[3] Employing effective AI/ML solutions can therefore go a long way in reducing fraud-related events and the resources required to investigate fraud cases.

4. Institutionalising the use of AI/ML in public health financing

To progress the use of and institutionalisation of AI/ML in health-care financing, some key areas mentioned below must be built and strengthened to guarantee a strong, suitable, and

[3] Smart contract is an agreement that is self-enforced as a code and managed by a blockchain.

[4] A false positive is an outcome where the model incorrectly predicts the positive class. And a false negative is an outcome where the model incorrectly predicts the negative class.

sustainable foundation. This will provide a conducive environment for the uptake of AI/ML in health insurance, by understanding the current needs and gaps better, so that effective and targeted use can be undertaken. These requirements may not be specific to health-care financing but are key to fostering an environment that can enable the use of ML in general, and hence in health and health insurance.

4.1 Political will and trust in governments

To adopt AI/ML technologies successfully for any public system, a committed political will is needed so that cooperation and coordination across government bodies can be established and common objectives can be laid down. This helps with building the public's trust in government so that they can be confident of transparency and accountability in public systems. If a trust deficit in public systems exists, it should be promptly identified and addressed to ensure active participation and acceptance from the public. Understanding the perceived challenges of AI/ML applications to effectively address public concerns will benefit governments and policymakers to tackle non-technical issues. When people can engage more transparently with these technologies, and gain confidence from suitable bodies/institutions that the use of AI/ML techniques will follow standard practices and appropriate norms and metrics, then they may no longer need to trust individual AIs and instead support and accept these advancements (Schwartz et al., 2022).

Perceived challenges of ML adoption in public health care

A study by Sun and Medaglia (2019) set out to explore the perceived challenges of ML adoption in the public health-care sector, drawing on empirical data from a case of ML adoption of IBM Watson in public health care in China. It noticed that a large majority of perceived challenges in this case were non-technical, and focused mainly on political, legal, and policy-related issues, along with data issues. Governments and policymakers should aim to assemble holistic narratives from all relevant stakeholder groups to build policy guidelines for ML in the public sector that are representative of diverse goals and objectives.

4.2 Data requirements and physical infrastructure

Machine learning, AI and big data technologies need massive quantities of data to run effectively and produce intended outcomes. Their performance is also dependent on the quality of data made available since poor data quality can lead to unintended or faulty outcomes. Understanding data requirements to enable the use of ML technologies is therefore an important first step in their application. Preparing data for use by AI/ML models or algorithms comprises the following broad steps: identifying the data source, undertaking data collection, data preparation, data cleaning and data management before applying ML algorithms.

In order to meet data requirements and aid with the longevity of these technologies, supporting physical infrastructure also needs to be provided (Willemink et al., 2020)validate, and test algorithms. The chief obstacles to development and clinical implementation of AI algorithms include availability of sufficiently large, curated, and representative training data that includes expert labeling (eg, annotations. Adequate data storage helps with data sharing and data transfer which can either be made available locally or externally. Data storage also helps ensure data security. Another important aspect is the provision of IT hardware to meet the optimal requirements as specified by the software in use or to be used.

As was also shared in a KII, “providing technological data architecture” is needed to adequately “host ML technologies”, including physical servers, so that data can be “kept in a secure location; and it could be either central or decentralised”.

Meeting data requirements and building the complementary physical infrastructure can therefore aid in building interoperable data systems, which can generate accurate results using transparent and integrated datasets. When medical datasets are fragmented, no uniform digitalization practice exists, and data sharing between stakeholders is not actively practiced, like in the case of India, identifying the scope for generating, storing, and using health-care data is a major step in promoting the use of advanced technologies.

4.3 ML biases and risk management

When ML systems make automated decisions based on biased data or biased inputs, biases in ML systems can emerge (Manyika et al., 2019). This can reduce the potential of these technologies by furthering mistrust and producing unintended, distorted outcomes (Manyika et al., 2019). Bias in modelling and usage can also lead to poor outcomes (Ferrer et al., 2021). Although ML biases often focus on statistical/ computational bias, other more serious biases that is, human and systemic biases (institutional/societal), can also plague the use of ML algorithms and should be assessed (Schwartz et al., 2022).

In the case of health insurance, health-care data, together with demographic data, including personal information (as needed), is used to run these algorithms. Therefore, if at the onset, datasets in themselves are highly fragmented, incomplete, or poorly representative of the populations they are supposed to cover, then biases in AI/ML models can occur.

“Building public confidence and greater democratic participation in AI systems requires ongoing development of, not just explainable AI, but of better Human-AI interaction methods and socio-technical platforms, tools and public engagement to increase critical public understanding and agency” (Ferrer et al., 2021).

There is a need to identify and understand these biases better so that appropriate steps can be taken to minimize anticipated and/or sudden negative impacts of AI/ML models. Effective collaboration between humans and AI concerning modelling, training and usage can help achieve trustworthy outcomes, and enable system and procedural transparency. When biases are identified, related risks can also be assessed and managed soundly.

4.4 Human resources

AI/ML technologies require experienced and skilled human resource support to be implemented successfully. This is needed not only to build these technologies and run them but also to ensure that human needs are identified and incorporated efficiently into these systems. With growing advancements and opportunities around core AI technologies, AI skilling will be needed to support the need for capacities around application-led concepts like robotics and natural language processing.

Regarding the use of AI/ML technologies in public health insurance, personal health-care data can be used to identify vulnerable populations, for a targeted approach by the government towards more equitable and better-quality health services. Therefore, it is important that policymakers, implementing bodies and government stakeholders are aptly informed of the challenges and gains related to AI/ML technologies, and have a clear understanding of what outputs can be achieved through this.

For these reasons, building a strong human resource pool is needed to aid in next steps for the use of AI/ML in health-care financing for UHC. It is also useful to build capacities within governments to reduce dependency on private organisations outside for various activities, like data management and analysis. In tandem with this, identifying financial capacities to meet these needs for human resources is also required to make adequate investments.

4.5 Governance arrangements

Accountability, transparency and explainability are crucial factors to consider when adopting ML technologies for public systems, especially as governments aim to meet public expectations inclusively. Ensuring expert and democratic oversight of algorithmic decision-making, both the benefits and negative outcomes of these technologies should be identified and well understood by public officials. Governments will need to stay abreast of rapid advancements in the area of AI/ML advancements making proactive investments in building responsible practices for AI/ML procurement, to avoid creating new risks and harm (World Economic Forum, 2019).

Protecting individuals' rights to privacy and enabling them to have more control over the use of their data should be a core focus when AI/ML processes are being established. Legal and regulatory frameworks are therefore critical components of effective systems to protect data privacy. It is important to gain acceptance from clients/patients on the use of AI/ML technologies in public health care, by explaining how their personal data will be used for the betterment of health services.

Since health-care data is personal, its access and ownership must be carefully determined. The intended use of data must always be clear, so that people understand and can trust the processes for which their data is being used. It is important to evaluate how confident and able governments can be in sharing patient data with other players in the market. It should also be assessed whether there are appropriate data governance mechanisms in place to safeguard against leakages or misuse of shared data. Although data sharing can open doors to new opportunities and collaborative learning, the practice should not be undertaken without a thorough risk assessment.

Requirements for data privacy and protection can be built into a framework designed for the use of AI/ML in public systems and assist in positive multi-stakeholder engagement. When people are more aware of who owns their data, who has access to it, and how it is being protected, they are more likely to trust both the institutions and people who are managing health technologies.

4.6 Attention to consumer perspective

In order to build trust and strengthen the infrastructure required for the application of AI/ML models, end users' knowledge gaps should be identified and correctly understood. Adequate steps should be taken to ensure that people (that is, the general public) are able to understand what is being undertaken with the introduction of ML in public systems. While a majority have optimistic opinions about its capability to improve human life, there are also legitimate concerns over ethical use, loss of control and undesired consequences by illegitimate usage of ML, particularly for sensitive areas like health care (Fritsch et al., 2022). If people are able to engage in a more transparent manner with these technologies, and gain confidence from suitable bodies/institutions that the use of ML techniques will follow standard practices and appropriate norms and metrics, then they can let go of needing to trust individual AIs and instead wholeheartedly support and accept these advancements (Schwartz et al., 2022).

Patient and public involvement

To alleviate the apprehensions surrounding the use of ML, Banerjee et al.(2022) introduces the concept of patient and public involvement (PPI) in research. While there is a rich history of PPI in health care, it has not been extensively applied in the context of modern ML. It is observed that being involved in a project helps build trust, though the level of involvement might vary from project to project. Banerjee et al. (2022) highlights that the idea of involving patients in health-care ML projects may help in the adoption and acceptance of these technologies.

The study proposes that ML algorithms should be co-designed with patients and health-care workers and that they should be involved in discussions around ML research applied to health care. It discusses that to build trust in ML algorithms, one also needs to consider the complex socio-technological milieu in which technological solutions reside. Trust needs to be built not only in ML algorithms, but also in the training data, software, and complex environment in which humans are situated. These include institutions and people and thereby trust in institutions and people is intimately linked to trust in health technologies. Avenues for future work include guidelines for patient and public involvement in ML health-care research for funding bodies and regulatory agencies.

5. Considerations – In the context of PMJAY

This global review explored various AI/ML technologies which may enable the functional operations of PMJAY to improve efficiency, increase coverage and improve the quality of service to beneficiaries. In line with this, we discuss below some useful areas that can be considered before implementing AI/ML methods, especially within resource constrained contexts. These are to assist in (i) striking a balance between policy goals and efficiency gains; (ii) deciding on financial investments in line with financial capacities and; (iii) taking informed decisions to first address "low-hanging fruit" challenges before more complex challenges are undertaken.

Enabling beneficiary identification and enrolment

A significant component of a solid foundation to enable the use of AI/ML technologies is the availability of a continuous stream of data that is complete, clean, and representative of the population its intended use is targeted. The PMJAY scheme targets the lowest 40% of the poor and vulnerable population in India, who also bear challenges such as seasonal migration and being "document-poor". The PMJAY scheme identifies beneficiaries using the SECC 2011 database, wherein many indicators to identify the socio-economic vulnerable populations are dynamic in nature. This may create hurdles to efficient beneficiary identification, and hence the coverage and enrolment of intended beneficiaries get poorly affected. This can result in potential hurdles for adopting AI/ML technologies since all data requirements cannot be fully met with respect to data quantity.

Advanced technologies can therefore be used to consolidate existing data sources from various central and state government platforms to identify the poor and vulnerable at present, maintain beneficiary databases which can be regularly updated, and in beneficiary enrolment and authentication. A KII respondent also interestingly suggested how limited but relevant questions in the next Census data collection process could be explored (like monthly average household expenditure, the existence of chronic or non-communicable diseases within a family, access to basic services like health and education etc., subscription to key developmental schemes), such that one exercise could serve multiple purposes.

Population mapping can be made possible by using several relevant databases to improve outreach and eligibility determination. ML options can be explored for self-verification processes by the beneficiaries to check their eligibility and then to enrol in the scheme using basic mobile phone calls or SMS services.

Example of self-verification assisted by ML technology
The Government of Togo is using a "MobileAid" approach to target aid for its poorest people in poor geographies of the country. The approach leverages ML and already available, ubiquitous data sources (for example, satellite imagery and cell phone metadata) to identify the poor. A self-enrolment tool is used to help with accessibility. People are encouraged to follow simple steps of dialling a designated number, providing their ID information, and answering a few short questions on the phone following which the tool matches these details against the poverty scores determined by a ML algorithm. Eligible applicants are then paid via mobile money, instantly, automatically, and remotely. (Marchenko and Chia S, 2022)

What also remains crucial here is facilitating and ensuring the use of unbiased data so that ML technologies can be undertaken effectively and help mobilise data to identify anomalies to minimise inclusion errors. Identifying and meeting data requirements will also enable maintenance of databases such that "clean rooms" or "sandboxes" can be created to share confidential health data for further research (medical/clinical/operational) which can inform financial planning and better resource allocation.

Building Information systems and physical infrastructure

Various platforms and data systems exist within the PMJAY IT ecosystem, each supporting specific functions, such as the Beneficiary Identification System (BIS), Transaction Management System (TMS) and Hospital Empanelment Module (HEM). Interoperability between these systems would enable an effective use of data, and different data sources (at the central or state government level) can be used to bridge any gaps in information needed for decision-making and running processes smoothly. This will enable a stronger application of AI/ML techniques as data requirements discussed above will be met, and algorithms will be able to function across data systems more seamlessly. It can also help with careful and timely updates to data across these systems, to ensure no eligible beneficiary "slips through the cracks" under PMJAY.

Building interoperability of data systems – Ethiopia
The Ethiopia Health Data Analytics Platform (EHDAP) is primarily implemented and used at the central level in Ethiopia by the Federal Ministry of Health (FMOH). Within EHDAP, the *Zenysis* software via an interoperability layer integrates data across systems, using data science techniques. Differences between integrated systems are harmonized, without needing to modify the fragmented systems themselves. The platform has successfully integrated data from ~15 fragmented systems and is able to provide more than 600 million data points from these systems, which are available and accessible for analysis through a single, easy-to-use platform (Digital Health Atlas, 2019).

Computational capacities may remain limited if the corresponding physical infrastructure is not able to support the use of advanced applications and algorithms. Required data infrastructure can be built when data sources are correctly identified, and data storage and management policies are well defined. Currently, infrastructure is a standing challenge in this area and many servers are hosted outside the country due to a lack of adequate cloud computing, high-speed internet and computing power (Srivastava, 2018).

Strengthening workforce

For PMJAY to effectively adopt ML technologies for its operations in public health insurance, a skills base that can support the successful application of these algorithms/models across key functional and support areas will be needed. A needs assessment for human resource requirements, in line with the scope and scale of technologies chosen, would enable appropriate capacities. Just as ML algorithms and models require continuous monitoring and learning, undertaking timely trainings will also be important to maintain a workforce that can evolve with the growing use of more advanced technologies by the government and build their data literacy.

Ensuring financial soundness

As the application of ML methods requires large financial investment, it may be more sustainable and achievable if "low hanging fruit" challenges[4] are tackled first, before significant investments are made by governments for public use. The development, adoption, and diffusion of technology in the public health-care sector, however, must be undertaken only after a robust analysis of financial soundness has been conducted. Long-term investment strategies should be made part of national guidelines, as needed, for the sustainability of digital and ML technologies (Tromp et al., 2022).

To ensure financial soundness of applied technologies, and aid in the selection of the right kind of technologies needed to achieve the objective of PMJAY, it may be useful to undertake health technology assessments (HTAs). This will assist the NHA in looking beyond a "use-

[5] Quick wins, or the most easily achieved of a set of goals

case" mentality and exploring ways that fit the Indian context better. A pilot cost-benefit approach could be adopted in the selection and deployment of ML technologies for focused objectives to assess their success before they are applied at large.

Countering ethical difficulties

India currently lacks a regulating body that oversees the impact of AI in the health-care sector, or health insurance in particular. One of the aims of such a regulating body would be to guide data security to prevent data misuse and abuse. Well-founded information is needed to support decisions on if and how an ML technology should be developed for public health insurance, how it can be acquired and used, and how consumers will benefit.

One positive initiative taken by the GoI is the draft ethical guidelines for the application of AI in biomedical research and health care, prepared by the Indian Council of Medical Research's (ICMR) Expert Group and coordinated by DHR-ICMR Artificial Intelligence Cell (ICMR, 2022). These guidelines highlight that AI for health, in any capacity, affects human life and can have grave consequences. India can also draw from various works undertaken on data privacy, security and/or protection in Europe such as the European Initiative on AI (launched by the European Commission) and the General Data Protection Regulation (GDPR). The GDPR is a tough privacy and security law which extends its obligations wherever EU citizens are being targeted, or their data is being collected. Amongst other key features, it comprises seven protection and accountability principles and also conditions for consent, which are key areas to be considered to counter ethical difficulties.

What is critical is that guidelines like these, drafted especially within and for the Indian context, are prioritised for implementation to guide all stakeholders in the development and deployment of responsible and reliable AI for health.

Considering a maturity model approach

To consider and promote the use of AI/ML technologies in public systems, it may be important to first identify which areas need AI/ML applications the most, why is it required and how they can be applied. A pilot approach, inclusive of cost-benefit analysis may help in understanding the financial investment required. Therefore, before expanding the application of AI/ML methods, a roadmap may be built based on a "maturity model" (MM) approach. A MM is a conceptual framework within this context would define the key domains and the associated baseline capacities needed to effectively adopt and manage ML technologies. It would provide a framework for organisations to benchmark their current state of readiness and to identify capacities they would need to build to mature to higher levels of organisational competency (Tarhan et al., 2020). The approach is based on an evolutionary pathway to achieve desired outcomes. The application of AI/ML methods for PMJAY can therefore start with smaller applications, identified within a high-priority domain, and on a pilot basis. Once the desired results are achieved (using learning cycles and course correction), and subject to a rigorous impact and cost-benefit analysis, appropriate applications could be expanded horizontally and vertically as the organisation's ML capacities mature.

References

Allal-Chérif, O., Simón-Moya, V., and Ballester, A. C. C. (2021). Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *Journal of Business Research*, *124*, 69–76. https://doi.org/10.1016/j.jbusres.2020.11.050

Amponsah, A. A., Adekoya, A. F., and Weyori, B. A. (2022). A novel fraud detection and prevention method for healthcare claim processing using machine learning and blockchain technology. *Decision Analytics Journal*, *4*, 100122. https://doi.org/10.1016/j.dajour.2022.100122

Asian Development Bank. (2021). *Digital Technologies for Government-Supported Health Insurance Systems in Asia and the Pacific: Experiences in the Region and Beyond* (0 ed.). Asian Development Bank. https://doi.org/10.22617/TCS210526

Banerjee, S., Alsop, P., Jones, L., and Cardinal, R. N. (2022). Patient and public involvement to build trust in artificial intelligence: A framework, tools, and case studies. *Patterns*, *3*(6), 100506. https://doi.org/10.1016/j.patter.2022.100506

Barclays. (2019, April 26). *Artificial Intelligence AI Payments | Barclays Corporate*. https://www.barclayscorporate.com/insights/innovation/ai-payments-revolution/

Bauder, R., da Rosa, R., and Khoshgoftaar, T. (2018). Identifying Medicare Provider Fraud with Unsupervised Machine Learning. *2018 IEEE International Conference on Information Reuse and Integration (IRI)*, 285–292. https://doi.org/10.1109/IRI.2018.00051

Blumenstock, J. (2021, July 13). Using Mobile Phone and Satellite Data to Target Emergency Cash Transfers. *CEGA*. https://medium.com/center-for-effective-global-action/using-mobile-phone-and-satellite-data-to-target-emergency-cash-transfers-f0651b2c1f3f

Choudhury, A., and Perumalla, S. (2021). Using machine learning to minimize delays caused by prior authorization: A brief report. *Cogent Engineering*, *8*(1), 1944961. https://doi.org/10.1080/23311916.2021.1944961

Digital Health Atlas. (2019, March 6). *Ethiopia Health Data Analytics Platform (EHDAP)*. https://digitalhealthatlas.org/en/-/projects/911/published

Ferrer, X., van Nuenen, T., Such, J. M., Coté, M., and Criado, N. (2021). Bias and Discrimination in AI: A cross-disciplinary perspective. *IEEE Technology and Society Magazine*, *40*(2), 72–80. https://doi.org/10.1109/MTS.2021.3056293

Fritsch, S. J., Blankenheim, A., Wahl, A., Hetfeld, P., Maassen, O., Deffge, S., Kunze, J., Rossaint, R., Riedel, M., Marx, G., and Bickenbach, J. (2022). Attitudes and perception of artificial intelligence in healthcare: A cross-sectional survey among patients. *DIGITAL HEALTH*, *8*, 20552076221116772. https://doi.org/10.1177/20552076221116772

Furtado, K. M., Raza, A., Mathur, D., Vaz, N., Agrawal, R., and Shroff, Z. C. (2022). The trust and insurance models of healthcare purchasing in the Ayushman Bharat Pradhan Mantri Jan Arogya Yojana in India: Early findings from case studies of two states. *BMC Health Services Research*, *22*, 1056. https://doi.org/10.1186/s12913-022-08407-2

Hanafy, M., and Ming, R. (2022). Classification of the Insureds Using Integrated Machine Learning Algorithms: A Comparative Study. *APPLIED ARTIFICIAL INTELLIGENCE*, 33. https://doi.org/10.1080/08839514.2021.2020489

Happe, L. E., Clark, D., Holliday, E., and Young, T. (2014). A systematic literature review assessing the directional impact of managed care formulary restrictions on medication adherence, clinical outcomes, economic outcomes, and health care resource utilization. *Journal of Managed Care and Specialty Pharmacy*, *20*(7), 677–684. https://doi.org/10.18553/jmcp.2014.20.7.677

Hartung, D. M., Touchette, D. R., Ketchum, K. L., Haxby, D. G., and Goldberg, B. W. (2004). Effects of a prior-authorization policy for celecoxib on medical service and prescription drug use in a managed care Medicaid population. *Clinical Therapeutics*, *26*(9), 1518–1532. https://doi.org/10.1016/j.clinthera.2004.09.013

Hassan, A. K. I., and Abraham, A. (2013). *Computational Intelligence Models for Insurance Fraud Detection: A Review of a Decade of Research*. 7.

Hehner, S. (2017). *Artificial intelligence in health insurance: Smart claims management with self-learning software | McKinsey*. https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/artificial-intelligence-in-health-insurance-smart-claims-management-with-self-learning-software

ICMR. (2022). *Draft Ethical Guidelines for Application of Artificial Intelligence in Biomedical Research and Healthcare*. indian Council of Medical Research. https://main.icmr.nic.in/sites/default/files/whats_new/AI_Ethical_Guidlines.pdf

Johnson, M., Albizri, A., and Harfouche, A. (2021). Responsible Artificial Intelligence in Healthcare: Predicting and Preventing Insurance Claim Denials for Economic and Social Wellbeing. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10137-5

Kruse, C. S., Goswamy, R., Raval, Y., and Marawi, S. (2016). Challenges and Opportunities of Big Data in Health Care: A Systematic Review. *JMIR Medical Informatics*, *4*(4). https://doi.org/10.2196/medinform.5359

Kurmanath, K. V. (2019, November 20). *How Telangana government authenticates beneficiaries using AI, ML, Big Data and Deep Learning tools*. https://www.thehindubusinessline.com/info-tech/how-telangana-government-authenticates-beneficiaries-using-ai-ml-big-data-and-deep-learning-tools/article30025564.ece

Manyika, J., Silberg, J., and Presten, B. (2019, October 25). *What Do We Do About the Biases in AI?* Harvard Business Review. https://hbr.org/2019/10/what-do-we-do-about-the-biases-in-ai

Marchenko, A., and Chia S, H. (2022, January 7). How MobileAid and Machine Learning-based Targeting can Complement Existing Social Protection Programs. *CEGA*. https://medium.com/center-for-effective-global-action/how-precision-aid-and-machine-learning-based-targeting-can-complement-existing-social-protection-de3bc3211fd2

Margolis, J. M., Johnston, S. S., Chu, B.-C., Onukwugha, E., Hvidsten, K., Alvir, J., Rossi, J. G., and Mullins, C. D. (2009). Effects of a Medicaid prior authorization policy for pregabalin. *The American Journal of Managed Care*, *15*(10), e95-102.

Mladenovic, S. S., Milovancevic, M., Mladenovic, I., Petrovic, J., Milovanovic, D., Petković, B., Resic, S., and Barjaktarović, M. (2020). Identification of the important variables for prediction of individual medical costs billed by health insurance. *Technology in Society*, *62*, 101307. https://doi.org/10.1016/j.techsoc.2020.101307

Ohlenburg, T. (2020). *AI IN SOCIAL PROTECTION – EXPLORING OPPORTUNITIES AND MITIGATING RISKS*. GIZ. https://socialprotection.org/sites/default/files/publications_files/GIZ_ADB_AI%20in%20social%20protection.pdf

PhilHealth. (2019, June 11). *PhilHealth adopts state-of-the-art technology to fight fraud*. https://www.philhealth.gov.ph/news/2019/adopts_tech.php

Planning Commission. (2011). *High Level Expart Group Report on Universal Health Coverage for India*. Planning Commission. http://planningcommission.nic.in/reports/genrep/rep_uhc0812.pdf

Rawat, S., Rawat, A., Kumar, D., and Sabitha, A. S. (2021). Application of machine learning and data visualization techniques for decision support in the insurance sector. *International Journal of Information Management Data Insights*, *1*(2), 100012. https://doi.org/10.1016/j.jjimei.2021.100012

Rawte, V., and Anuradha, G. (2015). Fraud detection in health insurance using data mining techniques. *2015 International Conference on Communication, Information and Computing Technology (ICCICT)*, 1–5. https://doi.org/10.1109/ICCICT.2015.7045689

Riikkinen, M., Saarijärvi, H., Sarlin, P., and Lähteenmäki, I. (2018). Using artificial intelligence to create value in insurance. *International Journal of Bank Marketing*, *36*(6), 1145–1168. https://doi.org/10.1108/IJBM-01-2017-0015

Schwartz, R., Vassilev, A., Greene, K., Perine, L., Burt, A., and Hall, P. (2022). *Towards a Standard for Identifying and Managing Bias in Artificial Intelligence*. National Institute of Standards and Technology. https://doi.org/10.6028/NIST.SP.1270

Srivastava, S. K. (2018). Artificial Intelligence: Way forward for India. *Journal of Information Systems and Technology Management*, *15*, 1–23. https://doi.org/10.4301/S1807-1775201815004

Sun, T. Q., and Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, *36*(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008

Tarhan, A. K., Garousi, V., Turetken, O., Söylemez, M., and Garossi, S. (2020). Maturity assessment and maturity models in health care: A multivocal literature review. *Digital Health*, *6*, 2055207620914772. https://doi.org/10.1177/2055207620914772

Tromp, J., Jindal, D., Redfern, J., Bhatt, A., Séverin, T., Banerjee, A., Ge, J., Itchhaporia, D., Jaarsma, T., Lanas, F., Lopez-Jimenez, F., Mohamed, A., Perel, P., Perez, G. E., Pinto, F., Vedanthan, R., Verstrael, A., Yeo, K. K., Zulfiya, K., … Cowie, M. R. (2022). World Heart Federation Roadmap for Digital Health in Cardiology. *Global Heart*, *17*(1), 61. https://doi.org/10.5334/gh.1141

UNDP. (2015). *Sustainable Development Goals | United Nations Development Programme*. UNDP. https://www.undp.org/sustainable-development-goals

Wang, Y. (P.). (2021). *Predictive machine learning for underwriting life and health insurance*. Actuarial Society of South Africa's 2021 Virtual Convention, South Africa. https://www.actuarialsociety.org.za/convention/wp-content/uploads/2021/10/2021-ASSA-Wang-FIN-reduced.pdf

WHO. (2021). *Promoting strategic purchasing*. https://www.who.int/activities/making-purchasing-more-strategic

WHO. (2022). *An assessment of the trust and insurance models of AB PM-JAY implementation in six states*. https://abdm.gov.in:8081/uploads/05_An_assessment_of_the_trust_and_insurance_models_of_PMJAY_implementation_in_six_states_0288d1d5dc.pdf

Willemink, M. J., Koszek, W. A., Hardell, C., Wu, J., Fleischmann, D., Harvey, H., Folio, L. R., Summers, R. M., Rubin, D. L., and Lungren, M. P. (2020). Preparing Medical Imaging Data for Machine Learning. *Radiology*, *295*(1), 4–15. https://doi.org/10.1148/radiol.2020192224

World Bank. (2022). *Universal Health Coverage* [Text/HTML]. World Bank. https://www.worldbank.org/en/topic/universalhealthcoverage

World Economic Forum. (2019). *Guidelines for AI Procurement*. World Economic Forum. https://www3.weforum.org/docs/WEF_Guidelines_for_AI_Procurement.pdf

Notes

Notes

Notes