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PM-JAY

सत्यमेव जयते
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World Health Organization
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Global review of the role of artificial intelligence and machine learning in health-care financing for UHC

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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.

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List of abbreviations

AB	Ayushman Bharat
ABDM	Ayushman Bharat Digital Mission
ADCD	additional data collection drives
AI	artificial intelligence
ALOS	average length of stay in hospitals
ANN	artificial neural network
BIS	Beneficiary Identification System
BPL	below poverty line
CAD	computer-aided detection
DSR	design science research
EHDAP	Ethiopia Health Data Analytics Platform
EHIF	Estonian Health Insurance Fund
EHIS	Estonian Health Information System
EHR	electronic health record
EMR	electronic medical record
EU	European Union
FMoH	Federal Ministry of Health
GDPR	General Data Protection Regulation
GoI	Government of India
HCD	human-centric design
HCV	hepatitis-c virus
HEM	hospital empanelment module
HR	human resources
HTA	health technology assessments
ICMR	Indian Council of Medical Research
IF	isolation forest
IoT	internet of things
ISA	implementation support agency
IT	information technology
KII	key informant interview
LMICs	low- and middle- income countries
LOF	local outlier factor
ML	machine learning
MoHFW	Ministry of Health and Family Welfare
NAFU	National Anti-Fraud Unit
NFHS	National Family Health Survey
NHA	National Health Authority

NLP	natural language processing
OPM	Oxford Policy Management
PMJAY	Pradhan Mantri Jan Arogya Yojana
PPI	patient and public involvement
RAI	responsible artificial intelligence
SDG	Sustainable Development Goal
SHA	State Health Authorities
TMS	Transaction Management System
ToR	terms of reference
TPA	third party administrator
TSU	technical support unit
UHC	universal health coverage
UN	United Nations
UPI	unified payments interface
UT	Union Territories
WHO	World Health Organization

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Introduction

1.1 Background

People in low- and middle- income countries (LMICs) generally rely on out-of-pocket spending for their medical expenses (Reshmi et al., 2021). This can result in significant financial shocks, particularly for poor and other vulnerable families. Health insurance is one of the interventions that has been suggested by expert committees as one of the ways to achieve Universal Health Coverage (UHC) to mitigate high secondary and tertiary care expenses for people, particularly the poor and vulnerable (Planning Commission, 2011).

In 2018, the Government of India (GoI) launched an ambitious health-care scheme called "Ayushman Bharat", which comprised the Pradhan Mantri Jan Arogya Yojana (PMJAY) as a key component. It was launched as a social health insurance scheme aiming to bring more than 107 million of the most vulnerable families in the country under the ambit of health insurance, covering a range of tertiary and secondary care.

Following the launch of PMJAY, the Ayushman Bharat Digital Mission (ABDM) was launched in September 2021 to strengthen the accessibility and equity of health services in India. The overall objective was to leverage the platform of information technology to support the existing health systems in a "citizen-centric" approach. Data-driven decision-making and infrastructure services, through digital systems, were a primary focus of ABDM, while also ensuring the security, confidentiality, and privacy of health-related personal information (NHA, 2021).

Moving in tandem with ABDM and PMJAY, a dual focus on a unified digital health system and health insurance emerge, providing a unique confluence for leveraging the latest in informational and computational technology for health and strategic purchasing towards a robust health system to provide quality of care. With PMJAY being the world's largest publicly funded health insurance scheme, sustainability is also an important goal to achieve in order to ensure equity and availability of services and quality of care. Sustainability requires accurate pricing, and this is hampered by the paucity of cost information required for systematic, evidence-based approaches to setting prices (Bahuguna et al., 2020).

Against this backdrop, this study is a global review with respect to 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 systems. The objective is to assess the benefits and challenges of AI and ML for the effective functioning of such systems towards sustainability, with the backdrop of the PMJAY scheme in India. With large amounts of relevant data[1] generated in India under the scheme, informed decision making can be promoted and strengthened by implementing the use of AI and ML in key strategic areas.

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[1] ToR

[2] https://www.pib.gov.in/PressReleasePage.aspx?PRID=1738169

1.2 Context setting

1.2.1 Concepts of AI-ML

The box below provides key definitions and concepts that are being used in this study, including Artificial Intelligence (AI) and Machine Learning (ML). It is important to emphasise that these definitions are not always clear cut and that differentiating between concepts can sometimes become difficult. For instance, when systems of ML techniques are sophisticated enough to be called AI is not clear.

Box 1: Definitions of key concepts
Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a goal, act in the physical or digital dimension to achieve this goal. They do this autonomously, by perceiving their environment through data acquisition, interpreting the collected data, processing this information, and deciding on the best action(s) to take to achieve the given goal. As a scientific discipline, AI includes several approaches and techniques, such as machine learning, machine reasoning, and robotics (AI-HLEG, 2019).
Machine learning (ML) techniques produce a numeric model, that is, a mathematical formula used to compute decisions from data. In essence, they are techniques to derive insights (“learn”) from data and, when defined very loosely, encompass any statistical analysis technique, including for example regressions. ML techniques can be categorized into supervised learning, unsupervised learning, and reinforcement learning. ML exhibits the experiential “learning” associated with human intelligence, while also having the capacity to learn and improve its analyses through the use of computational algorithms (Helm et al., 2020).
Supervised learning is a subcategory of ML and AI. It uses labelled datasets to train algorithms to classify data or predict outcomes accurately. It can be separated into two types of problems when data mining namely, classification and regression. Some common examples include neural networks, support vector machine (SVM), random forest and K-nearest neighbour (IBM Cloud Education, 2020a).
Unsupervised learning uses ML algorithms to analyse and cluster unlabelled datasets. Hidden patterns or data groupings are discovered by these algorithms without needing human intervention. Unsupervised learning models are mainly utilised for clustering, association and dimensionality reduction (IBM Cloud Education, 2020b).
Big data is often defined as data characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its management and analysis (De Mauro et al., 2016). Some common cases include GPS smartphone applications using GPS data in large quantities, sourced from satellite images and government agencies; meteorologists using data gathered from weather satellites and sensors all around the world.
Structured data is data which adheres to a pre-defined data model - a model of how data can be stored, analysed, and accessed. Often, this means data stored in a tabular format. It is the most traditional form of data storage and, crucially, allows for quick aggregation across databases. Common examples include excel files, SQL databases (Framework, 2019).

Unstructured data is data which is not organised in a pre-defined manner or one which does not have a pre-defined data model. This unstructured nature means that it cannot directly be read into standard analytical programs or frameworks for analysis. Rather, it needs to go through a management or data wrangling process to first structure it. Common examples include text data, video files, images, No-SQL databases (Framework, 2019).
Neural networks are a type of machine learning technique and lie at the core of deep learning algorithms. They are also known as artificial neural networks (ANN) or simulated neural networks (SNN). Their structure is inspired by the human brain, that is, mimicking the way biological neurons signal to one another (IBM Cloud Education, 2021b).
Natural language processing is a type of machine learning that deals with processing and analysing human language, for example, in text or recordings of spoken words. In its most advanced form, it is a branch of artificial intelligence which enables computers to understand text and spoken words in the same way as humans can. It combines computational linguistics with statistical, machine learning, and deep learning models. Some common examples include digital assistants, customer service chatbots and speech-to-text dictation software (IBM Cloud Education, 2021c).
Random forests are a commonly used machine learning technique which combines output of multiple decision trees to reach a single result. (IBM Cloud Education, 2021a).

In this review study, we are focusing on the application of AI and ML algorithms (that is, software) to data in health-care financing. Whether this has in some cases crossed the line from ML to AI or not, is not discussed in this report. *Please note: For consistency, we use the term "ML" across the rest of the report, which refers to applications of both AI and ML.*

1.2.2 ML in health care

ML methods are resulting in revolutionary changes across the health-care sector. Their application has been explored in various areas, including assistance in making clinical decisions, in personalised medicine, supporting diagnosis, maintaining electronic health records (EHRs), in medical robots and also in health-care system management (Guo and Li, 2018).

For example, IBM Watson is a leading ML health-care support system that is assisting doctors to make efficient decisions, with its machine learning and natural language processing capabilities. Radiology is one area where there has been substantial development using ML technology, due to the availability of large volumes of medical image data. AI systems are able to recognise complex patterns in imaging data and correspondingly provide quantitative assessments in an automated fashion (Hosny et al., 2018).

In another case, a project in Columbia utilised ML methods to identify potential individuals, who are likely to contract Hepatitis-C Virus (HCV), but not yet diagnosed, along with possible medicine requirement (Wilson et al., 2021). Early results from the project showed that AI-ML made these predictions with a higher degree of confidence.

In summary, the applications of ML methods have been used in health care to enhance diagnostic efficiency, to reach the patients with need, to monitor patients and suggest medication accordingly, and to use resources efficiently in a timely manner, among others.

With respect to health insurance, which is the focus of this review study, it is imperative that to effectively manage the health risk and outcomes of the population together, whilst maintaining financial viability of the scheme (public and private schemes) all the aspects of any health insurance scheme are effectively studied from the lens of ML applications, particularly for resource constrained economies. In order to derive the most of benefit from what ML application promise, it is also important to understand what the priority areas should be, what are requirements to establish a ML system, what are the possible gains and what could be the potential pitfalls.

Against this backdrop, this study aims to collate findings through a comprehensive literature review and stakeholder consultation to understand innovations and analyse learnings related to ML in public health-care financing globally.

1.3 Objectives and research questions

This study will contribute to the National Health Authority (NHA) in India's aim to better position itself to purchase quality services for PMJAY beneficiaries. It aims to provide emerging evidence to inform the design of reforms in ABDM, through an exploration of the potentials held by ML. The review aims to cover the following research questions:

- What are the types of ML applications prevalent in the health-care industry and publicly funded systems, particularly in health financing?
- What are the uses and related impacts of ML in health-care financing for UHC?
- What are some best practices/case studies of ML in health-care financing?
- What is needed in the institutionalization of the use of ML in health care financing (data processing, HR, governance arrangements), and related potential pitfalls and enabling factors?
- What are some emerging trends in the regulation and governance of ML or digital health more broadly within country health systems?

1.4 What this study is not covering

The preceding sections describe the context of this study, as well as the objectives and research questions it aims to answer. It is also important to define the boundaries of this work and to explain which areas are beyond its scope. There are four main points to be mentioned here:

- Firstly, the study does not review the opportunities and challenges of ML as they pertain to health-care delivery in general, and in particular, to diagnostics. There is broad literature and numerous case-studies on how ML can improve the detection or severity of certain diseases.[2] Assessing these applications was beyond the scope of this present study - although we have taken developments in this area into account in so far as they matter for health-care financing, more broadly.

[3] The scheme reached its 2-crore mark of hospital admissions in August 2021. Over 26,000 hospitals have been empanelled under the scheme until April 2022. Over 18 crore cards under the scheme have been generated and ₹36,500 crore been disbursed as claim amount until April 2022.

- Secondly, this study does not formulate or provide recommendations on a regulatory framework relating to the use of ML in health-care financing. However, ethical, and legal issues are very relevant for the appropriate use of these new technologies and the report only highlights some emerging trends related to governance and ethical use of ML applications in this regard. It does not conduct any in-depth research w.r.t these trends, and only shares indicatively what is being undertaken in this area.

- Thirdly, the limits of the corpus of literature reviewed for this study was defined by our conceptual framework (see section 2.1) and search strategy defined in section 2.3.1. Additionally, literature that was suggested during interviews with experts has also been reviewed. This review does not therefore constitute a systematic review.

- Fourthly, and finally, it is important to reiterate that this literature review was primarily guided and supported by secondary research and qualitative interviews. No quantitative data collection was conducted, or meta-analysis undertaken.

[4] https://viso.ai/applications/computer-vision-in-healthcare/

2

Approach and methodology

2.1. Conceptual framework

2.1.1 PMJAY and implementation models

The Pradhan Mantri Jan Arogya Yojana (PMJAY) is implemented through the state governments and union territories (UTs). It is completely funded by the government (that is, publicly funded) and costs are shared between central and state governments. The National Health Authority (NHA) of India is the agency which is in-charge of stewarding the scheme. Since states vary across various parameters such as disease burden, geographic spread of concerned population and available medical infrastructure, amongst others, the PMJAY scheme incorporates flexibility in its design and implementation. From the many parameters across which states are granted this flexibility, the implementation model is one such key parameter. NHA provides guidance to the states by developing mechanisms and support functions. This includes mechanisms for strategic purchasing of health care services, determine the central ceiling for premium, to regularly monitor and take course corrections actions for the implementation, capacity building of stakeholders, and develop and enforce compliance with standards for treatment quality and data security protocols.

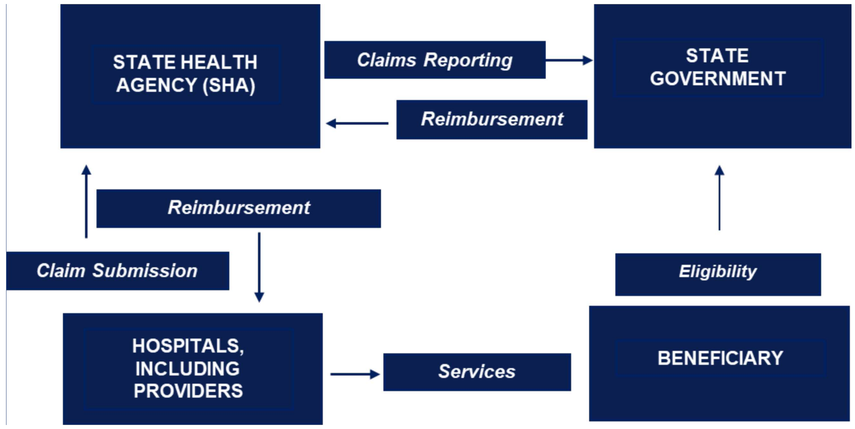
PMJAY offers states three implementation models namely, assurance model/trust model, insurance model and a mixed model, allowing states to involve private players as support agencies or a third-party administration service provider. These models are briefly illustrated below to help in understanding which entity assumes responsibility for risk and which entity performs the various functions in the insurance administration process.

Under the assurance/trust model, the PMJAY scheme is directly implemented by the State Health Agency (SHA). The central share of the contribution, under this model, is paid based on the actual cost of claims or the ceiling,[3] whichever is lower (Fig. 1).[4] The financial risk in this model is primarily borne by the government.

[5] The GoI sets a national ceiling amount per family, which is used to determine the maximum limit of the central share of the contribution.

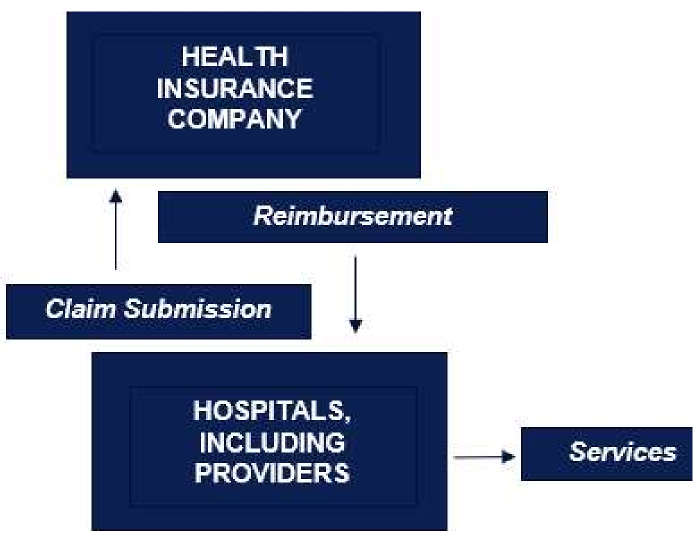
[6] https://nha.gov.in/PM-JAY#Financing

Fig. 1: Assurance/trust model under PMJAY scheme



In the insurance model, the SHA competitively selects an insurance company through a tendering process to manage the scheme in the state (Fig. 2). The financial risk for implementing the scheme is borne by the insurance company in this model. The insurance company can only obtain a limited percentage of the premium for their profit and administrative costs, as per defined mechanisms under PMJAY.[5] A flat premium per family (irrespective of the number of family members under PMJAY) is paid to the insurer based on the number of eligible families, by the state.[6]

Fig. 2: Insurance model under PMJAY scheme



Under the mixed model, the SHA engages both the assurance and insurance models in various capacities, allowing for convergence with the state scheme where applicable and offering more flexibility to the implementation of the PMJAY scheme.

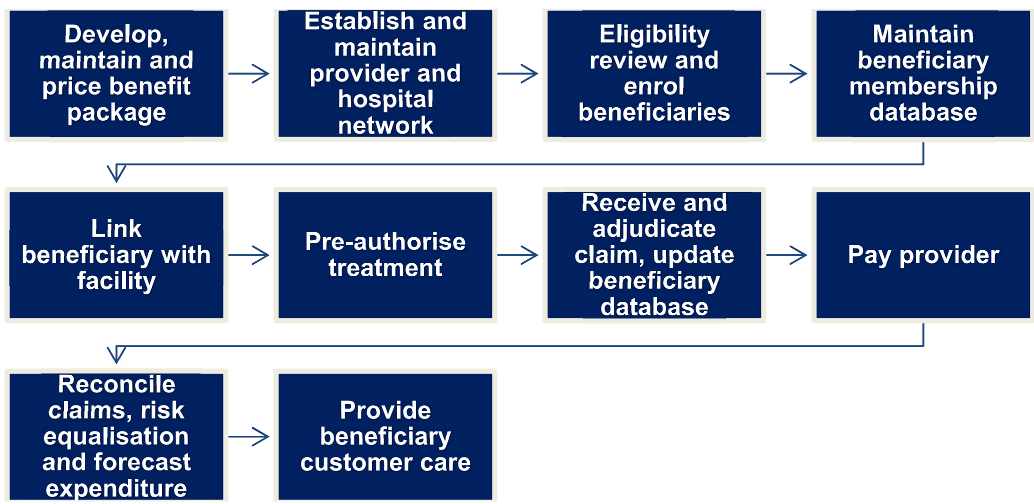
[8] https://nha.gov.in/PM-JAY#implementation
[9] https://nha.gov.in/PM-JAY#Financing

The overarching principles of a health insurance scheme, valid across these implementation models, include risk pooling, equity, solidarity, and empowerment (access, coverage), aiming to provide value-based care and protect households from catastrophic health expenditure.

2.1.2 Health insurance and related processes

The administration of health insurance is a complex process with high transaction volumes and large amounts of complex clinical, financial, and administrative data. The core value-adding processes of a publicly funded health insurance scheme are illustrated in Fig. 3 below.

Fig. 3: Core value-adding processes of a publicly funded health insurance scheme



Other support processes which run across the above functional areas include:

- Finance and risk management: Illustrative activities might include tracking claims expenditure, risk management, forecasting, accounting, fraud detection and mitigation
- Information systems: IT enablement, claims processing, clinical risk identifier, disease burden enabler, health outcome tracking.
- Governance: compliance with relevant legislation, patient safety, accreditation, quality of care, confidentiality
- Human resources: administrative, skills mix, staff management.

These support processes, along with the value adding processes described above, form part of our conceptual framework. This framework guided us in assessing possible ML applications to health-care financing. It also guided the narrative of the literature review for this study, to ensure we don't miss any key developments in this area. For a comprehensive synthesis of evidence, we grouped the above core value adding processes and support processes of the conceptual framework in the following broad functional categories: 1) Benefit design and pricing; 2) Beneficiary management; 3) Claims processing and 4) Provider selection and payment. Fraud Management is a support process, as stated above, which is also covered under the findings section.

The findings from this review aimed to offer insights on research questions by referring to each of these four functional categories. By doing so, the study attempted to cover the entire core value-adding process of publicly funded health insurance schemes, without missing any key steps in this process.

2.2. Methodology

To implement this study, we implemented a literature review and conducted expert interviews, as described below. This was done in a step-by-step process, following the broad steps described in Fig. 4.

Fig. 4: Broad methodology with key steps outlined.

Step 1
- An initial literature review, using a snowballing approach. The review was guided by the conceptual framwork and cross-cutting themes.
- Simultaneously, the identification process of key experts in this area was initiated, based on literature review and in consultation with WHO.

Step 2
- Developed the evidence matrix to summarize findings based on conceptual framework
- Initiated expert interviews process.

Step 3
- Expanded the review based on insights gained during expert interviews, while web-based and snowballing literature review continued.

Step 4
- Data extraction using an evidence matrix following secondary research.
- Continued expert interviews, including identification of more experts using a snowball sampling method.

Step 5
- Evidence synthesis across secondary and primary data (KIIs).
- Data analysis.

Step 6
- Preparation of draft report.
- Validation of findings/recommendations with WHO, NHA.

Step 7
- Dissemination of findings/recommendations with WHO, NHA.
- Finalising report, summary policy brief.

2.2.1 Secondary research and expert interviews

The secondary research exercise included a detailed round of desk search and literature review based on the conceptual framework discussed above, guided by the core value-adding processes of a publicly funded health insurance scheme (Fig. 3). The review also accounted for cross-cutting themes of regulating ML, ethics in ML and data management in ML. A snowball method was adopted to undertake the desk research, wherein key documents, and reports such as systematic reviews and meta-analyses, and other related published literature were identified pertaining to the subject area. This was followed by a focused search across databases, organisation websites, peer-reviewed journals, and other sources of grey literature to identify relevant literature and were included in this global review. In line with the objectives and scope of this study, the literature was screened with a focus on the application of ML in health care financing.

An initial round of desk research and preliminary literature review assisted the team in initiating stakeholder identification for expert interviews. This was also used to prepare tools for conducting expert interviews, and the semi-structured interview guides (lasting 45-60 minutes), which included questions and probes based on the research questions and conceptual framework of this review.

Key informants were identified based on their familiarity with the research topics and operated in the confluence of technology and health-care financing. The list of respondents was prepared in conjunction with WHO and validated by their team. The WHO team also facilitated introductory meetings/initial contacts with identified stakeholders, wherever feasible. Given the availability of KII respondents and time sensitivity of the study, the qualitative interviews were undertaken on an ongoing basis.

The expert interviews were initiated alongside the team undertaking desk research to collect secondary data. On receiving guidance and insights from experts in the field, the secondary research exercise remained dynamic in response to the same and was guided simultaneously to aptly determine what additional literature to include and exclude under this review. The review also included literature shared by some of the KII respondents, which are not available in public domain.

The review included literature published in 2009 and onward only. The geographic focus of this review included both developed and developing countries. Search themes and/or opportunities identified for adoption of ML techniques in health care financing were defined based on the conceptual framework discussed above in Section 2.1.

Box 2: Key search themes followed for literature search

- Benefit package development, pricing, and forecasting;
- Strategic purchasing, providers profiling (hospitals, labs, and other service providers), and reimbursement mechanisms;
- Beneficiary identification, enrolment, and profiling;
- Beneficiary database management, providers' database;
- Value based care, quality health care; universal health coverage;
- Health-care financing; out-of-pocket expenditures, health care spending;
- Enabling operational efficiencies through claims adjudication and claim processing;
- Enabling clinical risk management through claims risk identifier and forecasting;
- Enabling/strengthening grievance redressal mechanism through complaints management;
- AI governance, data protection norms and ethical considerations w.r.t use of AI-ML; fraud detection and prevention.

Potential enablers and challenges in the application of ML in health-care financing were also identified through secondary research in order to guide further work on considerations to implement ML applications, including the context of India.

The expert interviews included dialogue surrounding all the above-mentioned components. It was also crucial to discuss lessons learned from previous uses of ML in health care financing, along with recognising emerging trends in regulation and governance of ML within country health systems. The literature review and expert interviews also helped this review work in the identification of interesting cases/examples in this space.

2.3. Data

2.3.1 Literature covered under the review

This global review focused on secondary research by using an indicative list of key words to guide the researchers. This list of key words (see Annex A) was drafted based on the overall objective and the research questions this review aims to answer. Four researchers were engaged in the literature search and review exercise, and a data extraction matrix was used to extract useful information for careful analysis as illustrated in section 2.4 below.

The emphasis was on exploring both published, peer-reviewed literature and grey literature. Taylor and Francis database was used to search for published literature along with Google Scholar. Podcasts, private organisation websites (for example, IBM, KPMG, Deloitte), blog posts/articles, and international organisation websites (for example, WHO, Asian Development Bank, World Bank) were also carefully explored to direct us to relevant literature.

The literature search yielded useful results and a total of 185 documents were downloaded and reviewed by the researchers. This included articles, reports, original research papers, newspaper articles, webpages of relevant stakeholders and blog posts. A snowball approach, whereby literature referenced in papers already under review were then included in the review, also helped to direct researchers to other relevant literature from papers and articles being reviewed at a given time. We were also able to source some relevant literature via respondents in key informant interviews. The literature review covered both developed and developing countries.

2.3.2 KIIs covered under the review

A total of eleven KIIs were undertaken as part of the expert interviews. All interviews were conducted virtually and lasted between 45-60 minutes. In Table 1 we list the organisation's respondents were affiliated to.

Table 1: Institutional affiliations of KII respondents

Sl. No.	Organization	Country
1	University of Hawaii	United States of America
2	NUS Saw Swee Hock School of Public Health and Duke-NUS Medical school	Singapore
3	National Health Authority	India
4	BlueSquare	Belgium
5	DiGA Factory	Germany
6	Health Protection Surveillance Centre	Ireland
7	Hertie School of Governance	Germany
8	Hertie School of Governance	Germany
9	Clinton Health Access Initiative	India
10	Health Insurance Review and Assessment Service (HIRA)	South Korea
11	Hertie School of Governance	Germany

2.4. Data analysis

After data collection, a comprehensive evidence synthesis exercise was conducted to identify emerging evidence with respect to key research questions and to generate recommendations that can be considered and adapted to the Indian context in future.

Data was extracted from all relevant literature and captured using an evidence matrix, comprising key information such as:

- Author/authors; a publishing organisation
- Year of publication
- Geography covered
- Domains of health finance covered; private and/or public
- Components of and/or related to health insurance scheme(s)
- Type of data or ML technique(s) used
- Implementation challenges/barriers faced if any
- Mitigation strategies deployed if any
- Benefits identified w.r.t improvement in efficiency and effectiveness following use of ML
- Data governance, regulation, ethics, and related aspects discussed, if any
- Key takeaways for the country under consideration
- Any best practices/successful results discussed

The qualitative data collected from expert interviews was recorded, along with notes taken by the researchers, and studied in a systematic manner to identify driving inputs under the broad headings shared above. Evidence synthesis assisted in identifying common themes under application techniques, enablers, hurdles, and learnings, bridging the secondary research and expert interviews exercise. Case studies derived from best practices of ML in health-care financing were also prepared through the data analysis phase.

2.5 Caveats

Undertaking this review involved some limitations, which have been previously identified and are listed below:

- Broader public health applications of ML were limited to public health insurance for this study.

- Accessibility to relevant key informants for expert interviews could not be determined beforehand. The OPM team did their best to ensure all unnecessary delays were avoided, but unavailability of expert interviews/unwillingness to participate in line with the timeline of this project might have served as a hindrance in qualitative data collection.

- Grey literature was also used during the secondary research exercise for this study. Standard disadvantages associated with using grey literature in systematic reviews exist here too, in terms of objectivity, accuracy and intended audience to name a few (Baguss, 2019).

- Open access to all relevant literature online was not always available, limiting the desk review exercise in some instances. The OPM team reached out to the authors/relevant stakeholders requesting assistance with accessing relevant literature, where possible.

- Due to the rapidly evolving nature of the ML space, it was expected that there may be limited published literature particularly with respect to publicly funded health insurance. The team needed to primarily rely on grey literature with the limitations discussed above.

3

Application of ML in health insurance

This section responds to the following research questions:

- What are the types of ML applications prevalent in the health-care industry and publicly funded systems, particularly in health financing?
- What are the uses and related impacts of ML in health-care financing for UHC?
- What are some best practices/case studies of ML in health-care financing?

In this section, we consolidate the evidence gathered across study components (secondary research and Key Informant Interviews) through the lens of the broad functional categories of the conceptual framework presented in Section 2.1.2 as well as key research questions which guided our study design and overall approach.

3.1 Benefit design and pricing

Key takeaways

- ML can potentially assist in identifying crucial input for claim filing and acceptance and highlight inputs for which data needs to be collected accurately for estimating the cost of premium.
- ML algorithms for underwriting can assist state governments to understand the risk level of the population and quantify the risk. This can help in designing health packages as per the requirement of the population.
- ML can help in predicting total claim costs for an insurance company, faster and with more accuracy than human prediction using traditional statistical methods.

The cost of premium is one of the most important factors to consider for increasing the uptake of insurance. However, analysing the cost can be challenging as the regression method might not be able to factor in all the variables. ML models can help in using the vast amount of data that is collected by insurance companies but not utilized (Mladenovic et al., 2020; Rawat et al., 2021). In the current scenario, a large amount of digitalised data is being collected by health-care providers, pharmacies, and wearables. ML models can be used to assess past data and predict future costs and requirements (Goundar et al., 2020; Wang, 2021) and automate repetitive tasks (Bernard, 2022). In this section, we have discussed how ML can assist to develop, maintain and price benefit packages. ML can broadly help by:

- Analysing a large number of input factors and ranking them in order of relevance;
- Assisting in identifying factors that affect the premium cost;
- Underwriting and in cost prediction.

Most of the use case witnessed in this section has been in the private sector. However, it has an application in public insurance as the foundation of sustainability is accurate costing, specifically for Indian states which have opted for the insurance based or hybrid model under the PMJAY scheme. ML powered input can help states in a more accurate estimation of the premium paid for each beneficiary. It can also help the government to choose health benefits packages and avoid any disconnect between aspirational health plans and available financial resources.

3.1.1 Analyse input factors

A study conducted by Rawat et al. (2021) in the USA used feature selection techniques to identify "meaningful and decisive factors" for claim filing and acceptance. The study found that continuous variables (like age, BMI, and steps,) are more important than categorical variables for claim analysis. Another study by Mladenovic et al. (2020), which aimed to simplify the prediction process, analysed five input factors using a fuzzy inference system. The study found that using ML algorithms can help in identifying the most impactful factors with accuracy. This analysis showed that smoking had the highest impact on individual medical costs (Mladenovic et al., 2020).

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 accurate cost estimation. Additionally, feature selection techniques[7] can also help in the data pre-processing stage. It can eliminate irrelevant features and choose the best subset of attributes from an insurance database. It reduces the overfitting of data[8], increases the accuracy of the algorithm used and reduces the computation time (Hanafy and Ming, 2022; Taha et al., 2022). Under the PMJAY, this may be more useful for the state government which have opted for insurance model as it can help in a more accurate estimation of the cost and help in selecting the insurance provider.

3.1.2 Underwriting

Underwriting is the process of evaluating the risk involved in insuring people and setting a premium for the risk. Health insurance underwriting is generally a mix of rule-based and physical analysis by underwriters. This can be very time and cost-intensive because a) the rule-based models can include only a finite number of cases, and b) it requires a detailed process of risk analysis which includes medical tests, details of past conditions and processing many digital and physical paperwork (Wang, 2021). In private health insurance, the use of ML algorithms can help 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 the case of PMJAY, it is still necessary for central and state governments to understand the risk level of the population and quantify the risk. Under the insurance-based model of PMJAY the central government sets premium ceiling which are abided by the state government. However, it is observed that per unit utilization has been breached by many states[9]. In this context, ML can help in accurately determining premiums for states which have opted for insurance-based or hybrid model under PMJAY. It can also 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.

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[9] It is a process of automatically or manually selecting the subset of most appropriate and relevant features to be used in model building.

[10] The production of an analysis that corresponds too closely or exactly to a particular set of data and may therefore fail to fit to additional data or predict future observations reliably.

[11] https://www.news18.com/news/india/govt-to-increase-ceiling-rate-of-premium-paid-under-ayushman-bharat-to-rs-1500-4753127.html

A study by Hanafy and Ming (2022) conducted a research to understand whether different ML methods could be used to classify customers into different risk categories accurately, assuming that this would help to improve the way premiums are set. The study applied different algorithms like K-nearest Neighbour, Decision Tree, Random Forest. The study found that claims analysis using ML techniques could help in better understanding the customer strata and incorporate the findings in insurance policy enrolment, including the underwriting and approval or rejection stages (Hanafy and Ming, 2022). Another paper by Wang (2021) assessed whether predictive ML models can be used for underwriting in health insurance, especially for underwriting complicated medical conditions. The findings show that ML models have higher accuracy and precision score than rule-based algorithms. These models can also label cases that were riskier and needed review. The author points out that the limitation of the model is it requires a large amount of data for accurate performance (Wang, 2021).

These might be relevant for PMJAY, as the government is currently rolling out the Diagnosis Related Groupings pilot[10] where they are looking to account for comorbidities. Such ML models can potentially help in creating patient classification based on different factors like demographic, diagnostic and therapeutic attributes that can help determine the level of resource intensity for each group.

3.1.3 Insurance cost prediction

Medical claims comprise the total amount a company expected to pay in a year in the form of claims payment for insured. A study by Goundar et al. (2020) compared the level of accuracy between Artificial Neural Networks (ANN) and human prediction regarding anticipating annual medical claims based on the data of a private health insurance company in Fiji. The study found that the ML model reduced the forecasting error rate as compared to human prediction methods, that is, provided more accurate results than currently used methods (Goundar et al., 2020). Another study by Drewe-Boss et al. (2022) in Germany compared the application of an ML-based model with a regression model in cost prediction based on past data. It found that the neural network outperforms the regression-based model in predicting the change in health-care costs in one year.

3.2 Beneficiary management

Beneficiary management in health insurance includes beneficiary identification and enrolment, helping improve cost efficiency and customer satisfaction (Asian Development Bank, 2021). This section covers the following components from the conceptual framework: 1) eligibility review and enrol beneficiary; 2) maintain beneficiary membership database; and 3) provide beneficiary customer care. Accurate beneficiary management ensures efficient identification of beneficiaries (minimizing inclusion and exclusion errors) timely enrolment (ensuring patient access to treatment at the point of need), beneficiary authentication for avoiding redundant entries in beneficiary databases (for example, double insurance issues), overcoming coverage gaps and preventing fraud and abuse.

[12] Under PMJAY, there was pilot launch of Diagnosis Related Grouping (DRG) in 5 states of Chhattisgarh, Haryana, Kerala, Maharashtra, and Meghalaya, where patients are classified as per ICD-11 (International Classification of Disease) and ICHI (International Classification of Health Intervention). AB PM-JAY will be the first insurance scheme in the India to provider payment mechanism through DRG. https://pib.gov.in/PressReleseDetailm.aspx?PRID=1814806

Key takeaways
• Digital technologies have witnessed extensive use in beneficiary enrolment. This can be used to explore potential for the application of ML technologies going forward. • Accurate beneficiary identification is crucial in increasing coverage to intended beneficiaries. ML technologies can be used to better understand existing challenges in this area, for example, coverage gaps associated with migrating populations, and accurately mapping these vulnerable populations to enhance access to health-care services. • Natural language processing techniques are used in insurance chatbots to enhance customer care and satisfaction, through converting customer data into information to support customers' value creation.

Beneficiary identification*:* Use of 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 targeting of aid for poor populations in poor geographies, by searching and identifying people in need. An example is shared below in Box 3.

Box 3: Use case example - non health sector (Blumenstock, 2021)

Country: Togo (country in West Africa)

Program: Novissi, a social assistance program designed to provide emergency cash assistance to Togo's neediest families

Problem – A targeting challenge: The Government of Togo did not have a comprehensive social registry that could be used to directly identify and prioritize its poorest people. Moreover, the last census in the country was conducted in 2011 and that database also wasn't sufficient to help the government in determining who needed to be prioritised for assistance.

Use of ML technology to build solutions: To enable granular geographic targeting for the program, beyond national or regional level, a deep learning pipeline was used to identify the poorest 100 cantons in the country. A machine learning algorithm was trained using household survey-based estimates (nationally-representative) of poverty as "ground truth", to estimate the wealth of very small regions based on the geographic characteristics of that region. ML algorithms were also trained using mobile phone metadata to predict consumption, and generate consumption estimates for each of the 5.7 million mobile subscribers in the country.

Fairness: Several independent sources of survey data were used to calibrate and double-check the output of ML algorithms used. Algorithmic audits were conducted to examine if specific vulnerable subgroups were more likely to be excluded on the basis of the algorithm.

Potential use of ML technologies exclusively for beneficiary identification may involve ethical and privacy concerns, which need careful consideration before being used. For example, undertaking privacy impact assessment before deploying the use of facial recognition technology (FRT) would be important to ensure legislative or legal orders authorising the use of such technology are obtained (Kurmanath, 2019).

Beneficiary enrolment: Application of ML technologies in enrolling beneficiaries has been very limited, and not explored yet in the health-care sector. Social protection is one area in which use of ML has been explored, wherein comparison of a beneficiary's profile with the scheme or programme eligibility criteria allows for 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 or programme more responsive to changes in circumstances, so that enrolment of beneficiaries can be efficient and up-to-date (Ohlenburg, 2020).

Beneficiary enrolment has previously benefitted from the use of mobile apps (digital technologies) and the creation of citizen IDs and national level registries, to identify and enrol citizens in appropriate schemes. Indonesia, Kenya, and Nepal have used mobile enrolment solutions in order to extend the coverage of health insurance schemes (Asian Development Bank, 2021). Mobile JKN is a mobile app in Indonesia used to encourage self-enrolment. In Kenya, M-TIBA is used for self-enrolment and also by third party insurers who oversee specific population groups' enrolments. Health care providers and insurers use it for the secure digital administration of large-scale health schemes (Asian Development Bank, 2021). Use of these digital applications can be further explored to enable uptake of ML technologies by using relevant data generated from their use, which could aid in learning or training of models and algorithms and understand better the determinants surrounding correctly identifying beneficiaries.

Beneficiary authentication: Some interesting uses of ML technology have however been explored in beneficiary authentication, where existing databases are used to ensure that the right populations are being served by insurance schemes. For example, the Philippine Health Insurance Corporation (PhilHealth) worked on a "proof of concept" with technology providers for "liveness checks" and "identity authentication" which was rolled out in 2020 in its offices and participating health facilities (PhilHealth, 2019). The aim was to use "liveness checks" to validate if a member or dependent was still alive or had expired (during confinement), following the COVID-19 pandemic, to ensure that related health services were rolled out correctly to people whose identity could be properly authenticated (PhilHealth, 2019).

Box 4: Beneficiary authentication using ML technology (Kurmanath, 2019)

In India, Telangana's state government is exploring usage of ML and big data technologies in authenticating beneficiaries. Realtime Digital Authentication of Identity (RTDAI) has been implemented by the government, which employs software to verify photos and demographic details in databases, helping to avoid the need to physically authenticate people; without also needing any special hardware at the user end.

The Pensioners Life Certificate Authentication using a Selfie (PLCS) method, used by the state government, is a three-level authentication process which comprises an AI-based liveness check solution and a ML-based demographic comparison solution. Users can authenticate themselves from anywhere and anytime post one-time registration and authentication. These ML and deep learning solutions aim to use information piled up in public data systems to quickly check details submitted by users.

The state government, a few years ago, reported a ~93% success rate in authenticating pensioners using this technology, which offers scope to use this in other areas also such as authenticating beneficiaries of public health insurance schemes.

"The system would learn over a period of time and the success rate could be improved as it learns" (Commissioner, Electronic Service Delivery).

Beneficiary database: Integrating unique beneficiary identification mechanisms within health insurance programs can improve effectiveness and efficiency in increasing coverage. It can lead to the creation of a credible beneficiary database, that 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 use of ML technologies, by offering large quantities of data that is complete, representative, and up to date. It is envisaged that future ML technologies will be able to aid with monitoring and tracking beneficiary databases to minimise inclusion[11] and exclusion[12] errors encountered in administration. 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 in India, maintaining accessible and efficient beneficiary databases will be important in offering greater coverage and efficiency of their public health schemes.

Beneficiary customer care: 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. Recent technological and digital developments have opened new avenues for customer data utilization in insurance services. One form of this data transformation is automated chatbots that provide convenient access to data leveraged through a discussion-like interface.

[13] Inclusion error due to implementation (IE) is the proportion of a programme's beneficiaries who do not meet the eligibility criteria but do receive social transfers.

[14] Exclusion error due to implementation) (EE) is the proportion of eligible individuals or households in a programme area who do meet the eligibility criteria but do not receive social transfers.

The study, Riikkinen et al. (2018), was amongst the first to systematically identify and assess chatbots currently being used by insurance actors in the market. It discussed three complementary perspectives in regard to creating and supporting customers' value creation using insurance chatbots, namely service logic, AI, and reverse use of customer data. Reverse use of customer data comprised shifting attention from using customer data for the benefit of the firm (private) towards converting customer data into information to support customers' value creation. Prominent examples of latest technology being used in ML chatbots were identified, including approaches for learning word representations[13] and text classification[14]. Service logic was used to understand customer's value creation using a theoretical lens. ML technology and chatbots were therefore used to create value in insurance for customers by functioning at the intersection of theoretical and technological perspectives mentioned above, along with industry phenomenon, that is, efficient transfer of resources and processes using digitalization.

In 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. Use of regional language based chatbots for FAQs and grievance redressal can further help to overcome language and cultural barriers and enhance customer engagement, particularly in rural India. It can also support the hospitals by answering questions about the PMJAY program, claim submissions, and reimbursement processes, reducing the administrative burden.

3.3 Claims processing

Key takeaways
• ML techniques can help in proactively identifying the post-hospitalization needs and starting the pre-authorization process for the subsequent treatment at the in-patient stage.
• ML can also facilitate the claim submission process by proactively identifying coding and billing errors and decreasing the claim processing time by filtering out any unusual requests prior to processing.
• Natural language processing systems can identify the accuracy of the documents by reading image and text data to ensure that the claim document have minimal errors.

As per the conceptual framework of this study, this section will discuss the use of ML for pre-authorisation and claim adjudication.

[15] Word representation aims to represent a word with a vector. It helps ML models better understand, categorize, or generate text in NLP tasks.

[16] Automatically dividing written texts, speech, or recordings into shorter, topically coherent segments, used in improving information retrieval or speech recognition. (https://landbot.io/blog/natural-language-processing-chatbot)a

Claim processing refers to the procedure of reviewing claims and auditing them, and then deciding what the next processing steps are. This is a highly cumbersome area - as per a study based in Germany as many as 70% of claims are flagged as doubtful, out of which only 10% of cases are objected (Hehner, 2017). As per an assessment of PMJAY in 6 states, claim rejection rates were 2.3% in states that opted for insurance model and 4.8% in states which opted for trust mode in 2019-20. It was higher for states like J&K (6.4%), Himachal Pradesh (5.5%), and Uttar Pradesh (5.5%) (WHO, 2022). Many of the claims were also rejected because of errors in the forms like coding and billing errors (Johnson et al., 2021).

Another challenge in claim processing is the pre-authorization process.[15] 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)increases the inpatient length of stay, and affects patient health. Our study implements predictive analytics for the early prediction of the PAC discharge disposition to reduce the deferments caused by prior authorization and in turn minimizes the inpatient length of stay, and inpatient stay expenses. We conducted a group discussion involving 25 patient care facilitators (PCFs and increased medical expenses (Choudhury and Perumalla, 2021; Margolis et al., 2009). This is because the requirement is frequently known after the treatment is over and the process only starts after the discharge decision is taken by the care provider (Choudhury and Perumalla, 2021). A recent study based in India also highlighted that late initiation and lack of documentation are the primary reason for rejection of pre-authorization request (WHO, 2022). 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. In the PM-JAY context this can also lead to significant out of pocket expenditure that vitiates objectives of the scheme. Also, there is still a chance of error where incorrect claims are paid. ML can provide a solution to prevent claim denials and reduce the processing time for preauthorization.

Box 5: Responsible artificial intelligence in health care: predicting and preventing insurance claim denials for economic and social wellbeing (Johnson et al., 2021)

This study utilizes Design Science Research (DSR) paradigm and develops a Responsible Artificial Intelligence (RAI) solution to help hospital administrators identify potentially denied claims before they are filed while masking patients' private information and keeping the data secure.

The study applied different ML-based solutions to a large-scale dataset of insurance claims of various companies in the US. The results show a high accuracy rate of 83.35% in identifying if claims will be denied or accepted. The findings also show that the most common reasons for claim denials are "medical necessity, a mismatch between procedure and diagnostic codes and unbundling."

Some of the limitations of the study are that the model was only tested in a single hospital, also the study did not consider insurance fraud in the analysis.

[17] Pre-authorization is a process which requires health-care 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.

A report by McKinsey and Company, based in Germany, points out that “smart algorithms” can reduce the burden of manpower in claim management (Hehner, 2017). These algorithms filter any unusual request, prioritise them based on the amount and suggest reasons for rejecting the claims. The system is built in a way that it learns with every new claim and thus the rate of errors reduces over time (Hehner, 2017).

Box 6: 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: 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.

Another study by Choudhury and Perumalla (2021) shows that an ML model (named CHAID algorithm)[16] can help in pre-authorization for post-acute care/ post-hospitalization. In this study, the prediction model is integrated into the existing clinical workflow. This can assist in predicting post-acute care services required by patients during the in-patient stage and enable doctors to commence the process of pre-authorization early. Without the use of ML, this process would only start after the discharge decision is taken. The ML model thereby reduces delays caused due to pre-authorization by 22% (Choudhury and Perumalla, 2021).

Additionally, experience from Taiwan documented by Lee, et al. (2022) has shown the importance of AI-ML and big data in processing of large volume of claims. This is especially relevant when large amounts of structure or unstructured data is available at hand. AI-ML can provide the necessary tools to help claims review and fraud detection in such cases. In the case of Taiwan, this was facilitated by the masses of data available to the NHIA on varying aspects of patient health through the NHI MediCloud system. The NHI MediCloud system consists of longitudinal data of all patient records over time with medical professionals being able to read patients’ records of medications, surgeries, tests and exams, medical images, history of drug allergies, etc., through a secure virtual private network.

[18] Chi-squared automatic interaction detector

Box 7: Digital health-care in Taiwan: innovations of National Health Insurance

In Taiwan (Hsueh, 2022), the National Health Insurance Administration (NHIA) introduced big data analytics and AI tools to improve the efficacy of claim reviews. In order to get the quality inputs NHAI has set up a cloud-based system to encourage medical institutions to updated data and images promptly. AI is employed to monitor the quality of images and reports before claims are uploaded, ensuring adherence to standards and formats. These AI tools also analyse structured and unstructured data, including medical claims, test results, and examination images, to detect discrepancies and fraudulent behaviour. Furthermore, AI technology has been developed to identify duplicate or similar images submitted for review, assisting agency in detecting potential cases of fraud. For instance, The NHIA has discovered some sporadic cases from contracted medical institutions that were suspected of submitting identical images as review materials for different cases. To address this issue, an advanced AI-powered reviewing tool was created specifically for dental and cataract images. This tool employs automated algorithms to swiftly detect and flag duplicate or highly similar images, aiding physicians in identifying potential instances of image fraud within seconds. Lastly, NHAI also provides de-identified data to researchers for further development of AI models for providing efficient healthcare.

Overall, digital claim management has the potential to reduce expenses for insurance companies by reducing cost related human resources and setting up faster processes at different stages (Bernard, 2022). In the context of India, the PMJAY has established digital measures for claim settlement which is a pre-requisite for applying any ML-based processes. However, a mixed methods study conducted in Uttar Pradesh and Jharkhand shows that some of the claim management processes are manual and large number of queries are raised by the insurance agencies, which increases the processing time (Furtado et al., 2022). One of the KII respondents from India also emphasised the need for 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. ML can help in these processes by using natural language processing systems (Wang, 2021). Application of these systems can potentially become more efficient once PMJAY introduces and systematizes International Statistical Classification of Diseases and Related Health Problems (ICD-11) coding (NHA, 2022).

3.4 Provider selection and payment

Large numbers of suppliers/providers exist in the market that buyers can choose from. In case of a public health insurance scheme in India, the government can choose from a mix of public and private health-care providers and insurers. This makes the government the buyer in this scenario. It is known that large quantities of data exist across these stakeholders, which carry potential for added value, but which is seldom harnessed (Allal-Chérif et al., 2021). In-depth analytical assessment of these large datasets can aid the purchasing function for buyers by making more efficient and transparent use of this data to draw relevant inferences for buyers in place of humans having to work through the same. It can therefore aid with provider selection, and consequently with provider payment.

In health care, 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, 2021b). Core aspects of purchasing, as stated in Mathauer et al. (2017), include information management systems, benefit package design and mixed provider payment systems. A strategic approach to purchasing can help improve quality of health service delivery and enhance transparency and accountability for providers and purchasers (Mathauer et al., 2017).

The private sector experience can assist in identifying possible ways that the public sector can explore w.r.t the application of ML in provider selection. For example, supplier selection using matching systems in the private sector assist buyers to select a supplier from a large pool by recommending 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.

These examples are indicative of possibilities that the public sector can explore since uptake in public health insurance doesn't exist right now. The government can carefully determine efficient providers using relevant indicators such as average length of stay in hospitals (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, based on their respective health risk burdens to ensure the right population can be provided quality health-care services by adequately empowering providers.

Making payments to providers/suppliers from buyers can also benefit from use of ML technologies to ensure efficient and timely processing. In 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

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

Key takeaways

- Insurance frauds features among the top-most expensive crimes and lead to adverse implications for UHC.
- Unsupervised ML holds promise for detecting new type of frauds, but more work is needed to improve specificity and minimize false positives in detecting fraudulent providers.
- Using a hybrid of supervised and unsupervised methods holds the potential to make duplicate claim's identification process more scalable.

Insurance fraud is ranked second in the list of expensive crimes in the United States, with health-care fraud being the second highest among all insurance fraud (Kumaraswamy et al., 2022). In India, health-care fraud is of significant concern with the health-care industry overall losing approximately INR 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).

Box 8: Different types of health insurance frauds

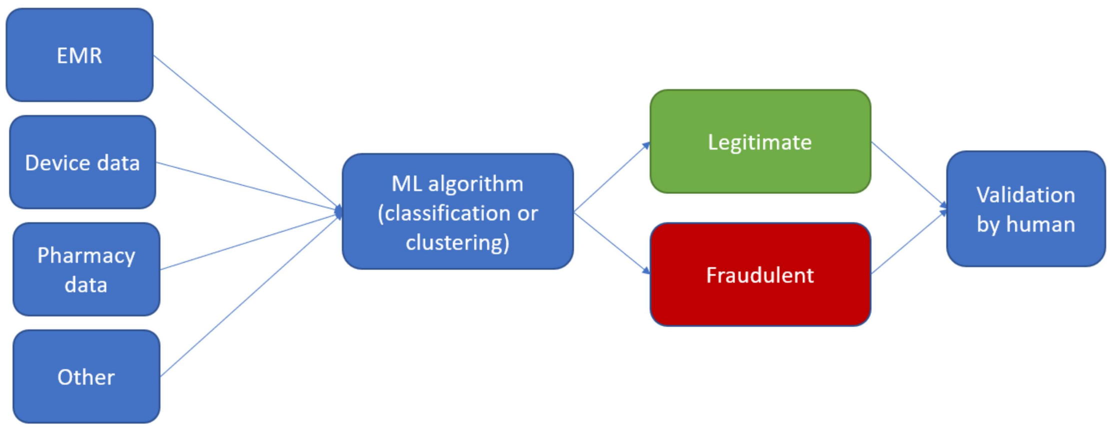
- **Billing for services not rendered**: Billing an insurance company for health-care services or products that were not rendered.
- **Upcoding of services/products**: Billing an insurance company for services or products that are more expensive than the actual procedure performed.
- **Duplicate claims**: Charging an insurance company twice for the same service rendered.
- **Unnecessary services**: Filing claims which in no way apply to the condition of a patient or not in the quantity.
- **Over-servicing:** Filing claims for services which may apply to the condition or diagnosis but not necessarily clinically indicated.
- **Other types of fraud:** For example, beneficiary eligibility fraud, means test fraud.

The different manifestations of insurance frauds described in the box above lead to depleting efficiency and trust in the system (Kapadiya et al., 2022; Pai et al., 2016). 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). Additionally, within a public no-pay environment, fraud increases the cost of government providing the package of benefits, hampers expansion (coverage) of the programme and threatens sustainability. To combat this kind of societal threat, there is a need for health-care fraud detection systems to evolve.

During the KIIs conducted as part of this study, most of the respondents seemed to concur that fraud, and within that, the simple identification of duplicate claims could be a basic first step as insurers begin to think of building further competency in this space.

Several ML methods are being used to assist in detecting fraud in an efficient and effective manner (Johnson and Khoshgoftaar, 2019). As depicted in Fig. 5, ML methods can use data from various sources like electronic medical records (EMRs), devices, pharmacy, labs and imaging to help in classification, clustering, outlier detection and identification of legitimate and fraudulent cases based on patterns in the data (Hassan and Abraham, 2013).

Fig. 5: Fraud detection process



As discussed by Pai et al. (2016), ML techniques have been explored to combat the problem of fraud in health insurance. Of particular interest is the fact that there is a fundamental issue with using either supervised or unsupervised learning methods when detecting fraud (see Box 1 for a description of these concepts).

On the one hand, supervised learning approaches can be trained to identify fraud very efficiently from previously labelled data. This means that they can identify existing forms of fraud and can often do so more efficiently or more accurately than other statistical methods. On the other hand, however, supervised learning methods cannot identify new types of fraud because they have not previously been trained to identify these methods. Two major shortcomings therefore are that supervised learning models cannot detect new types of fraud and significant resources are required to derive the labelled training samples to be used to train the model in the first place.

Unsupervised learning methods, on the contrary, do not rely on previously labelled data. They can therefore help to identify new, unusual, and previously unidentified patterns in data. This might not always lead to identifying fraud - as new patterns can simply be legitimate new activities - but can help to raise attention where needed.

3.5.1 Application of ML in identifying fraudulent medical providers

In the context of fraud being an ongoing issue in the *US Medicare program* and resulting in higher health-care costs for beneficiaries, Bauder et al. (2018) conducted an empirical study of various unsupervised machine learning methods to detect outliers and indicating fraudulent medical providers. The ML method here used provider's procedures performed and associated payments to assess behaviour indicating normal behaviour or potential fraud. The providers flagged as possibly fraudulent were then investigated further to assess culpability. Findings from this study suggest that using ML techniques helps reduce the time and number of resources needed to identify fraud *by narrowing down the providers that require additional investigation.* The LOF40 (local outlier factor) method outperformed all other methods covered in this paper, having correctly detected 50% of fraudulent providers and 68% of non-fraudulent providers. The isolation forest (IF) method performed poorly but had the highest sensitivity at the optimal decision threshold and correctly identified 71% of fraudulent providers, although it also had a high false positive rate. While the unsupervised ML techniques hold promise in detecting fraudulent providers, there is more work needed to improve specificity[17] and avoid too many false positives.[18]

3.5.2 Application of ML for fraud detection in claims processing lifecycle

The claims process in the insurance industry is risk prone and the industry overall spends USD 2 billion to identify fraud and compliance issues in the process (KPMG, 2017). One of the common fraud practices is submitting duplicate claims. In general, duplicate claims are not identical, and have some minor changes in date or invoice number for instance, which makes it difficult to identify the duplication. The use of ML can be helpful in this case. Rawte and Anuradha (2015) recommends using evolving clustering method (EVM) for identifying duplicate claims. In this method the diseases are first clustered by type and then classified to detect any duplicate claims within each cluster. This process is a hybrid of supervised and unsupervised methods and holds the potential to make the process more scalable (Rawte and Anuradha, 2015). However, this paper only made a theoretical proposition, without testing it on any existing database or making claims about the accuracy of the method.

With respect to Ghana's National Health Insurance Scheme (NHIS), Amponsah et al. (2022) proposed a novel method to detect and prevent fraud by using a combination of Blockchain technology and machine learning algorithm. The study focused on leveraging machine learning to equip the blockchain smart contract[19] in detecting and preventing fraud in health insurance claims processing. Machine learning methods were proposed because they can turn domain-specific data into knowledge and then provide efficient classification and predictive models that can be used in the future. Amponsah et al. (2022) used Decision Tree algorithms to classify original NHIS claims related data to extract the patterns of fraud. The extracted knowledge was then implemented in blockchain smart contract which equips it with decision-making capability and allows the smart contract to detect fraud in health insurance claims using real data. The results from this study showed that the proposed system enhanced the blockchain smart contract's ability to detect fraud with an accuracy of 97.96% and hence future claims could be classified with an error of approximately 2%.

Experience from Estonia on role of AI-ML in fraud detection has also been highlighted in the literature (World Health Organization, 2023), wherein automated fraud detection and review has helped improve over process turn around time and helped realize efficiency gains.

[19] Sensitivity in Machine Learning can be described as the metric used for evaluating a model's ability to predict the true positives of each available category.

[20] 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.

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

Box 9: Fraud detection in claims processing in Estonia Health Insurance Fund (EHIF)

The WHO country report on Estonia's health insurance (WHO, 2023) emphasizes on ML-based systems for fraud detection in claims management process. ML is employed to automate the verification of claims and other digital documents, improving the accuracy and speed of reimbursement processes.

EHIF also uses both supervised and unsupervised model to identify fraud as per the predefined rules and flag any outliers or unusual cases (this includes checking for incompatibility of patient characteristics and clinical information (gender or age versus diagnosis or procedure), discrepancies in quantities of services, and deviation from averages length of stay/average reimbursement amount per case) for further investigation. This is helpful because, prior to the introduction of ML, only a fraction of claims underwent manual fraud checks, making it unclear how many fraudulent claims went undetected. With ML, the EHIF now processes all incoming claims and assigns a likelihood score to potentially flawed claims. Only claims with the highest scores are forwarded for manual inspection. This help in saving time, cost, and human resources.

The report cautions against overemphasizing efficiency checks of procedures and treatment choices by providers. This emphasis might lead to insufficient attention to equity and quality aspects of care. It highlights the importance of finding a balance between ML-driven fraud detection and human resources-based claims review to ensure quality care to the patients.

The Government of India has been taking proactive measures to propagate the use of technology to remove any scope of fraud in the PMJAY (ET Healthworld, 2022). The NHA includes a fraud detection cell at the national level called the National Anti-Fraud Unit (NAFU) and the State Anti-Fraud Unit (SAFU) at the state level to detect and flag fraudulent transactions through AI systems (NITI Aayog, 2021). When the AI system flags a case, the reason for flagging is forwarded to the SAFU and investigated. While the patient always receives treatment without delay, the payment is disbursed to the hospital only after all the queries related to the case are adequately resolved. Special efforts are made to minimize false positives[20] in the system (NITI Aayog, 2021). The NAFU has recently been able to successfully detect the suspected fraud using the e-cards on the basis of algorithms developed internally (Perappadan, 2020).

In summary, employing effective ML solutions discussed above, can go a long way towards reducing fraud-related events and also the resources required to investigate possible fraud cases. It is also important to highlight the need to detect frauds in a preventive manner rather than post facto so that leakage of claim revenues can be prevented. By doing so, ML solutions can thereby reduce redundancies, and mitigate financial losses associated with health insurance frauds, and contribute positively towards the shared ambition of Universal Health Coverage.

[22] 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.

3

Institutionalising the use of ML in health insurance

This section responds to the following research questions:

- What is needed in the institutionalization of the use of ML in health care financing (data processing, HR, governance arrangements), and related potential pitfalls and enabling factors?
- What are some emerging trends in the regulation and governance of ML or digital health more broadly within country health systems?

Although use of ML in health insurance remains limited globally, especially when compared to its use for clinical efficiency/operations, it is crucial that countries who are expanding into this area now learn from existing experiences of other countries to minimize their learning curves and avoid expected hindrances as much as possible. In order to introduce and institutionalise the use of ML in health care financing, some key requirements must be in order to ensure a strong, suitable, and sustainable foundation. These have been highlighted in the research question stated above and were also discussed as part of our expert interviews.

The KIIs illuminated why these areas need careful attention and investment before ML technologies can be adopted across all possible areas of public health-care financing in a full-fledged manner. While secondary research did provide some insight into what is required for adoption of ML technologies, this study gathered more evidence on this via KIIs since use of ML in health-care financing is a new area of work and a lot of the information is tacit knowledge.

In this section, we discuss such requirements and how they could lead to pitfalls in case of their absence, and as enabling factors when duly accounted for. These requirements may not be specific to health-care financing but are key to fostering an environment that can enable use of ML in general, and hence in health and health insurance.

4.1 Political will and trust in governments

For publicly funded health care to achieve its goals and ensure effective and efficient provision of health care to all those in need, it is essential that the citizens place their trust in governments and are confident of transparency and accountability in public systems. In India, the health-care system is mixed, comprising both public and private health-care service providers (Chokshi et al., 2016). The governance and operations are divided between the central and state governments. Cooperation and coordination across government spheres will be helpful and defining common objectives will aid in establishing strong political will to adopt new ways of working, along with ensuring corrective measures.

In this case, when discussing the application of ML in health insurance, any trust deficits in the public health system (if any) should be aptly identified and addressed to ensure active participation and acceptance from the public. As was also discussed in one of our expert interviews, more than technical will to implement these technologies in health, strong political will is needed to determine what ML outputs will be used for and how.

Box 10: 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.

Fear of democratic backsliding[21] was also expressed in one of our discussions with an expert, wherein concerns were shared on change of governments in some cases leading to altered objectives for using technology for public advancement. The respondent shared, "I think one of the scariest things that we haven't got our heads around is that once you've got a whole system set up and working beautifully and everything is going great, a change of government could be able to use exactly the same system for bad."

As was commented by one expert, "Even if the system you've got in place is 100% locked down and perfect, they [the public] would need to feel comfortable that that's the case and especially as it's a public system. One has to have that sort of transparency and there would need to be a way of describing the system to the people who are affected by it, so that they feel comfortable that their data is being used in a way that's safe and transparent and appropriate and that the output of the system isn't going to unfairly affect them."

4.2 Data and physical infrastructure requirements

Machine learning, AI and big data technologies all need large 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 outcomes. Understanding data requirements to enable the use of ML technologies is therefore an important first step in their application.

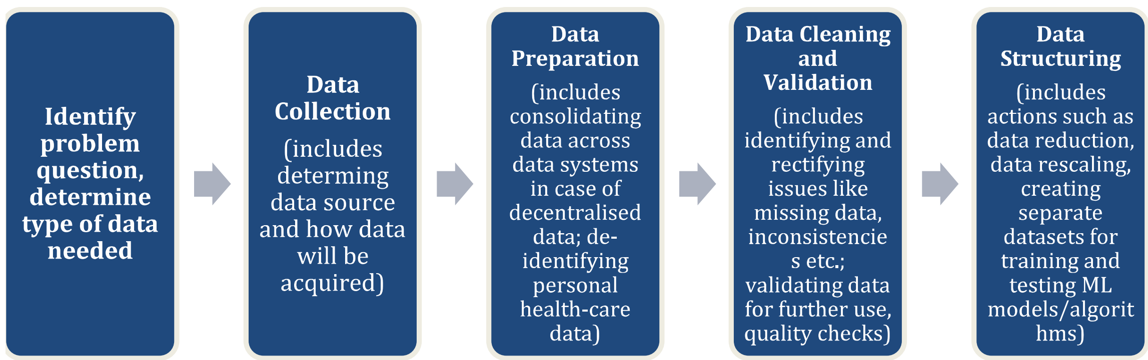
Structured and unstructured data are two broad categories of data, defined above in section 1.2.1, which are used purposively across different ML techniques. In case of health care, a mix of structured, unstructured, and semi-structured data exists ranging from doctors' notes, prescriptions, and medical reports to imaging data like X-rays, CT scans and MRI scans. Electronic health records (EHRs) provide digitally stored health information of patients and populations for use across health-care systems. In India, medical datasets are fragmented, there is no uniform digitalization practice and in general, data is not shared between different stakeholders, including hospitals and doctors. The lack of transparency and disintegrated

[23] State-led debilitation or elimination of the political institutions sustaining an existing democracy

datasets can lead to inaccurate results (Ho et al., 2020; Parry and Aneja, 2020)

Therefore, it isn't sufficient to only identify the type of data (w.r.t quantity and quality of data) needed for a given ML model or algorithm. Different steps are involved in identifying and prepping data to be used by ML technology, as has been illustrated in Fig. 6 below (Lawton, 2022). An expert interview also highlighted the need for careful investment in the same stating, "But there's a couple of things, which are very obvious, one needs skilled people to program these algorithms. But the data itself needs to be very clean. So, the challenge in many cases is that people don't invest in the boring work of cleaning data or actually checking the data quality."

Fig. 6: Preparing data for use by ML model/algorithm



In order to meet these data requirements and aid with longevity of these technologies, supporting physical infrastructure also has to be provided (Willemink et al., 2020). This helps with tending to data security concerns also. Adequate data storage helps with data sharing and data transfer as well, which can be either made available locally or externally. 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".

When data and related physical infrastructure requirements are met, robust and useful databases can be maintained to ensure a continuous flow of information to ML models to generate dependable outputs.

4.3 ML biases and risk management

When ML systems make automated decisions based on biased on biased data or biased inputs, biases in ML systems emerge (Manyika et al., 2019). This can reduce potential of these technologies by furthering mistrust and producing unintended, distorted outcomes (Manyika et al., 2019). Unfair or unequal treatment of certain populations based on certain characteristics such as income, education, may be caused due to these biases, leading to digital discrimination (Ferrer et al., 2021). For example, flawed data sampling may lead to over or under representation of certain groups in training data that can skew results from the use of a ML algorithm or model. One such case is that of facial analysis technologies reflecting a higher error rate for minorities, and particularly for minority women, in case of gender classification systems, as discussed in (Buolamwini and Gebru, 2018). Bias in modelling and bias in usage can also lead to poor outcomes (Ferrer et al., 2021).

Although ML biases often focus on statistical/computational bias,[24] 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 addition, ML risk management is important to minimize anticipated and sudden negative impacts of ML models. In an expert interview, pertinent questions in this area were also raised - “How can we minimise errors resulting from use of technology, and how can we consequently minimise conflict (if any) arising from these errors?”. In cases where health inequities already exist, use of ML technology for decision making may reinforce or further these inequities, if inherent biases aren’t identified and accounted for.

As discussed in the paper by Schwartz et al. (2022), it is also important to consider human-AI configuration and how ‘human-in-the-loop’ processes can be implemented to ensure that computational, human and/or systemic biases are not amplified. This can help achieve trustworthy outcomes and enable system and procedural transparency. Understanding the organizational, operational, and societal environment in which an ML system is to be implemented can also help empower an ML’s life cycle and deliver intended results which account for factors such as values, fairness, ethics, and bias (Schwartz et al., 2022).

> “Building public confidence and greater democratic participation in AI systems requires on-going 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)

Useful and reliable outcomes from ML algorithms also depend on the quality and quantity of data being provided to these systems. In the case of health insurance, health-care data, together with demographic data, including personal information (as needed), will be required to run these algorithms. If datasets in use are highly fragmented, incomplete, or poorly representative of the populations they are intended to cover, then biases can emerge which may unfairly target individuals, ethnic or minority groups, or certain sections of society. As was highlighted by Eneyew (2019), data fragmentation across various systems such as hospitals, electronic health records (EHRs), labs and financial IT systems can hinder integrating all required data across these database systems into an integrated pool, which can potentially cause less than optimal use of ML models.

On similar lines as above, a KII respondent shared: "if your data is biased in a certain way - let's say if you have fraud claims and you know the prevalence of people of a certain ethnic group is overrepresented in those fraud claims within your data - your algorithm will consider ethnicity as a factor, and it could lead to unjust inclusion/ exclusions."

Another KII respondent shared concerns regarding data biases poorly affecting forecasting outcomes, saying, "The biggest problem of course with all forecasting, including some of these risk things, we are just talking about, is that they may disproportionately affect some kind of minority."

A strong foundational system is therefore needed to support advanced applications. If adequate data requirements aren't met, the reliability of ML applications and related outputs could be questioned and significant investments in these technologies will not deliver intended benefits. Protecting investment in ML applications requires ML biases and risks are appropriately managed. *"AI-ML engines are very expensive and require huge amounts of reliable data as input."*

4.4 Human resources

ML technologies require appropriate human resource and skills support to be implemented successfully. Skilled and experienced human personnel are needed not only to build these technologies and run them, but also to ensure human needs are identified and incorporated efficiently into these systems. Building a strong human resource pool will aid with informing policy makers, governments, and other stakeholders of the potential and challenges related with ML technologies, and what outputs can be achieved with their proper use. Capacity building within governments is also needed to build technical rigor, in order to reduce dependency on private organisations outside for various activities, like data management and analysis.

In light of this, it is possible that developing countries, when compared to developed countries, may have to address a situation of skill shortage in this area. As briefly discussed in TechGig, (2020), there is a growing need and demand for AI skills in the Indian market. Opportunities around building awareness on core AI technologies and use-cases was also identified, so that AI skilling can support the need for capacities around application-led concepts like Speech recognition, computer vision, robotics, natural language processing. One way this can be made possible is by standardising AI curriculum for undergraduate and postgraduate programs in the country (TechGig, 2020). Additionally, a basic understanding on digital health can also be included as a part of medical graduates curriculum.

It is also important to identify the need for human resources so that appropriate skills and capacities can be built and strengthened to meet requirements for the technologies in use. As highlighted in an interview, there's need for both front-end and back-end developers with respect to building and using ML technologies, and how differentiating between data engineers and data scientists is an easy step to determine apt human resource requirements. Another interviewee highlighted how people can be encouraged and scouted to work with governments, who have the technical prowess in order to build in-house capacity by "setting up recruitment drives", since depending on the private sector to solve human resource related problems will not work.

Appropriate skills are also needed to assist with the complex task of explaining ML models to the public including providers. Building trust and gaining acceptance from end users/clients/patients (in case of health care) can occur when humans can interact beyond machines and algorithms, to understand these technologies and related outputs better.

As an interviewee mentions, "[…] why people find it harder to accept technology. Because they think they [govt.] is spending a lot of money on machines, which they [govt.] should have to spend on people. And at the end of the day, there still have to be those human intermediaries who are helping citizens understand how to use the system, so that people aren't disempowering".

In light of this, it is important to also understand the financial capacities needed to build human capacities, as was stated in another interview, "[…] and to do capacity building, there is a need of money to hire a person who can clean that data out, bring it together and do and automate the process in such a way that one doesn't have to do it over and over again".

It is important that health care workers are also kept up to date with the use of constantly changing technology, techniques, and a constantly moving standards of care. Due to the constant evolution of technology, there exist populations of individuals lacking specific skills; as such this is also a significant continuing barrier to the implementation of big data methods (Kruse et al., 2016).

4.5 Governance arrangements

Accountability, transparency and explainability are important factors to keep in mind when adopting ML technologies for public systems, especially as governments aim to meet public expectations in an inclusive way. In order to ensure expert and democratic oversight of algorithmic decision-making, both benefits and negative outcomes must be identified and assessed by public officials. It would be helpful for governments if investments are made timely in building responsible practices for ML procurement, in order to counter any possible risks and harm (World Economic Forum, 2019). As highlighted collectively in our expert interviews, data access, ownership, sharing, privacy, and protection are deeply crucial in ensuring that ML technologies can be used fairly, justly, and effectively in achieving intended outcomes.

Principles for ML development and use

Although no specific ethical principles for the use of ML in health insurance have been proposed for adoption worldwide, numerous principles and guidelines have been developed for "ethical" application of ML for health. These are nonetheless important for all stakeholders engaged in the development, deployment, and evaluation of AI technologies used in health care, ranging from clinicians to policymakers in health authorities, and local and national governments. (WHO, 2021a)

A 2021 WHO report titled Ethics and Governance of Artificial Intelligence for Health highlighted some key ethical principles for use of AI for health, aimed to encourage and assist the public sector to keep pace with technological advancements through legislation and regulation. These included the following: a) protect autonomy; b) promote human wellbeing, human safety, and public interest; c) ensure transparency, explainability and intelligibility; d) foster responsibility and accountability; e) ensure inclusiveness and equity; and f) promote responsive and sustainable AI.

Responsible AI is also discussed by Wearn et al. (2019), wherein the framework comprises of five principles - transparency, justice, non-maleficence, accountability, and privacy. These principles aim to make existing ML applications transparent and ethical, while ensuring user expectations are confirmed and aligned with state laws and societal norms.

Regulations

Regulation of AI technologies is likely to be developed and implemented by health regulatory authorities responsible for ensuring the safety, efficacy, and appropriate use of technologies for health care and therapeutic development. A WHO Expert group has identified areas that should be considered by stakeholders in examining new AI technologies which include documentation and transparency, risk management and the life-cycle approach, data quality, analytical and clinical validation, engagement and collaboration, and privacy and data protection. (WHO, 2021a)

(Ho et al., 2020) illustrates how a clear and effective data governance framework is critical, wherein legal standards must be enacted as necessary. Adopting a human centric approach in the design and use of big data analytics and ML was stated to be encouraged and incentivised for insurers. The paper illuminated the essential need for clear and accountable processes on what information can be used and how, so that transparency can be established for the people on how their data may be used by governments (Ho et al., 2020). Insurers and governance bodies must focus on ensuring that these technologies don't worsen existing inequalities, and erode trust of relevant stakeholders (Ho et al., 2020).

> As stated during a KII, "Under certain schemes, people are allowed to get services in empaneled public and private hospitals. But then who's going to collect the data? Is the private sector equipped to do that? Are they going to do it according to the government guidelines? Are they going to follow the rules? Are they going to follow data security policies, ethical policies that the government has outlined? Are their systems going to be compatible with the similar systems of the government? How is data transfer going to happen between these systems?"

Generally, the African continent's digital transformation strategy encourages African Union Member States to "have adequate regulation; particularly around data governance and digital platforms, to ensure that trust is preserved in the digitalization". (WHO, 2021a)

Data privacy

Since health-care data is personal, its access and ownership must be carefully determined. Intended use of data must always be clear, so that people understand and can trust the processes for which their data is being used.

As interestingly stated in an expert interview on the subject, "So, I think any ethics policies should be centered around control and the possibilities that exist to utilize the data, not necessarily about consent. Patients and generally people are more than OK to share their data for the public or common good. We just assume as researchers that they might not be OK with it. But there are surveys which showed that they are more than willing to share data for the common good. The question is, to what extent that data can be used against or in favor of the person. So, the ethical policies need to be around control of the data, not exactly around consent."

Another KII respondent, discussed possible issues related to data sharing, especially between governments and outside parties (for example, private software company), wherein red tape and bureaucracy could create hindrances in easy and quick sharing. It is important to evaluate how confident and able governments can be in sharing patient data with other players in the market, and whether there are appropriate data governance mechanisms in place to ensure no leakages or misuse of shared data. Although data sharing can open doors to new opportunities and collaborative learning, the practice shouldn't be undertaken without a thorough risk assessment.

Protecting individual's rights to privacy and enabling them to have more control over the use of their data should be a core focus when ML processes are being established. Legal and regulatory frameworks are therefore critical components of effective systems to protect data privacy. Blockchain technology in some cases has proven useful in addressing certain types of privacy concerns. For example, the Estonian nationwide Health Information System (EHIS) hosts many central registers and databases and utilizes several nationwide registers. It also comprises a patient portal which patients can use to log into their "*my health*" portal wherein they can view information on which health-care provider has retrieved which information from their medical record. This way every citizen can see in real-time who is looking at their health data, which helps tremendously with establishing norms and rules regarding data privacy and access (Asian Development Bank, 2021).

Safeguarding and protecting individual privacy is not only recognized as a legal requirement in many countries but is also important to enable people to control sensitive information about themselves and self-determination (respect for their autonomy) and to avoid harm.

Data security

A data security breach or misuse can lead to discrimination and violation of the privacy of individuals (Alami et al., 2020)

A KII participant also highlighted concerns around cybersecurity, stating how one cannot discuss ML without remembering the digital technology. The expert shared, "You cannot talk about AI without remembering the digital technology. And that means somebody could hack into it. Hence, cybersecurity is absolutely essential...How do you set it up in such a way that you can't know things that would be inappropriate for you to know, but you're still able to do your job."

Over one hundred countries have enacted data protection laws. One well-known set of data protection laws is the General Data Protection Regulation (GDPR) of the European Union (EU); in the USA, the Health Insurance Portability and Accountability Act, enacted in 1996, applies to privacy and to the security of health data. (WHO, 2021a)

The Ibero-American Data Protection Network, which consists of 22 data protection authorities in Portugal and Spain and in Mexico and other countries in Central and South America and the Caribbean, has issued General Recommendations for the Processing of Personal Data in Artificial Intelligence and specific guidelines for compliance with the principles and rights that govern the protection of personal data in AI projects (WHO, 2021a).

4.6 Attention to consumer perspective

In order to build trust and strengthen the infrastructure required for the application of 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. Users lack technical know-how, and the complex nature of ML applications can sometimes make it difficult to convey the potential benefits and applications of these technologies.

This knowledge gap could lead to apprehensions and questions. 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). A lack of focus on consumer perspectives in this space was expressed in one of our expert interviews - "people should be made aware of who owns their data, who has access to it, and how it is being protected".

Another interviewee shared their thoughts on how the general public is often welcoming of the use of their data if it is targeted for public good and collective gains. However, it is still crucial that they understand the potential of this data and what can be achieved with it when harnessed in the right ways. If data privacy and protection are built into the framework designed for the use of ML in public health-care systems or public health insurance systems, then ML governance and regulations can assist in positive multi-stakeholder engagement.

While ML has become increasingly relevant in the social debate in recent years, the level of public knowledge about ML is often low and its perception is not exclusively positive. 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).

Modern health-care aims for participation and cooperation of patients, often described under the term "patient empowerment". Unlike the perception of health-care professionals, the attitudes of patients and their companions have been of less interest so far. (Fritsch et al., 2022) further reported that the general perception also seems to differ between certain groups of respondents. Elderly, female, or less educated persons, as well as those having a low technical affinity, have a more sceptical view on ML in health care.

Box 11: 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 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 how in order 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

Discussion - In the context of PMJAY

The McKinsey Global Institute Digitization Index has found that despite AI"s potential, uptake in the health sector has been slow compared to other sectors, even in industrialized nations in Europe and the United States (McKinsey, 2016). When governments investigate the viability of adopting ML, careful attention should be paid to the trade-off between efficiency gains and policy goals. ML technologies require significant financial investment and the choice of where to spend limited resources should align with policy objectives, especially within resource constrained contexts. Investment in ML technologies should also form part of established priority setting frameworks which balance financial investment with anticipated gains, and which also compare a possible investment in ML technologies with other possible investments within the health system. The literature and key informants also emphasise that starting to adopt ML technologies is a dynamic and evolving process as opposed to a once-off event, as needs and capabilities change with time. A government may initially utilise fairly simple technologies to address so called "low-hanging fruit" challenges, and with growing capabilities can evolve into tackling more complex challenges (Wilson et al., 2021).

The PMJAY scheme is the GoI's flagship health insurance scheme that covers a range of tertiary and secondary care for the socioeconomically deprived population. This review explores which ML technologies may enable the functional operations of PMJAY to improve efficiency, increase coverage and improve quality of service to beneficiaries. In line with this, some key considerations for the NHA/PMJAY are discussed below.

5.1 Enabling beneficiary identification and enrolment

Building a strong and robust foundation will help enable the use of ML technologies. One significant component of this foundation is the availability of a continuous stream of data that is complete, clean, and representative of the population its intended use is targeted towards. Since the PMJAY scheme was rolled out for the bottom 40% of poor and vulnerable population, which in about 10.74 crore households, it is of utmost importance that data on all eligible beneficiaries is collected, stored, protected, and made available for further use and research. Digital tools and integrating the health insurance scheme with national IDs has proven beneficial for the scheme, and it is important that this opportunity is harnessed accurately for greater benefit (World Bank, 2018). However, the coverage/enrolment of the intended beneficiaries under the scheme remains limited (Sharma, 2021).

In India, ~80% of all employed persons are engaged in the informal sector, making inclusive development a challenge (Wire Staff, 2018). The country's poor have also been called "document-poor", with as many as 51.4% households in the poorest quartile and 58.4% in the next quartile (poor) not possessing either an Antyodaya Anna Yojana or a Below Poverty Line (BPL) ration card in 2004-05, as per an analysis of the National Sample Survey data (Rukmini, 2020). The PMJAY scheme identities beneficiaries as per the SECC 2011 database, where many of the indicators to identify socio-economic vulnerable are dynamic in nature. Many states, along with SECC 2011, use other state-level databases as suited. This is indicative of the potential lack of updated and complete data that truly represents the country"s population that the public health insurance schemes wish to serve. There is therefore a need for efficient and updated data collection and tracking initiatives, which can strengthen data streams across the country and enable the application of ML techniques.

As one of the experts shared, "I question whether we're really ready to put that burden on the data streams that currently exist. The data streams are quite weak from some states, quite good from other states. And so, if you have unreliable data streams, then of course you have garbage in, garbage out. If you put "garbage" in an AI engine, your inferences that it builds and the pattern that it finds, are not really actionable."

Since collecting and maintaining data in a populous country like India can be challenging, an interesting consideration to aid with the process was suggested by a KII respondent, wherein including limited but relevant questions in the next Census data collection process could be explored (like monthly average household expenditure, existence of chronic or non-communicable diseases within family, access to basic services like health and education etc., subscription to key developmental schemes), such that one exercise could serve multiple purposes. It could help with saving time and aptly identifying eligible beneficiaries for the PMJAY scheme, since databases used currently as part of the scheme are old and could be out-dated. It was also discussed how consolidating existing government databases (for example, National Food Security Act database) with other databases maintained as part of state-specific government schemes could help with improved targeting with respect to poor and vulnerable sections of the population.

In this regards, more advanced technologies can be used for population mapping purposes to reach more people extensively and carefully determine their eligibility, based on several recent databases, so that all targeted populations can be enrolled to avail benefits under PMJAY. 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.

Box 12: 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)

However, measures should be taken to unbiased estimates by the ML models. Some ML models might be consciously or unconsciously trained on datasets that do not represent the entire population or are biased towards the most vulnerable (Alami et al., 2020). For instance, a widely used medical algorithm in the US has shown racial bias by assigning lower level of risk to black patients for similar illness as compared to a white patient (Ho et al., 2020). Therefore, only when unbiased data is generated, use of ML technologies can be undertaken effectively. This will also 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.

5.2 Building information systems and physical infrastructure

Various platforms and data systems exist within the PMJAY IT ecosystem, each with its own purpose. The Beneficiary Identification System (BIS) is used to approve/reject applications entitled for benefits under the scheme by applying the pre-defined identification criteria. The Transaction Management System (TMS) is used to register beneficiaries for availing treatments in hospital, raising pre-authorization, filing treatment details, and raising claim to third-party administrators (TPAs) for further processing of claim requests sent by hospitals/providers. Claims approval and payments to the hospitals/providers through banks is also undertaken on the TMS. The Hospital Empanelment Module (HEM) is a web-based platform developed for registration of a health-care provider willing to get empaneled under PMJAY.

Building interoperability between these systems will enable exchange and purposive use of data, and different data sources could be used to bridge any gaps in information needed for decision making and running processes smoothly. It will also help with careful and timely updates to data across these systems, so as to ensure no eligible beneficiary “slips through the cracks”, like in the case of additional data collection drives (ADCD) conducted under PMJAY. As also stated in an interview, “You need one solution, or if you even have three solutions, you need them to [be able to] speak with each other”, highlighting how interacting information systems are useful to apply technological solutions to complex problems. Decentralized data can be more effectively used if systems are interoperable, especially since the PMJAY scheme uses the SECC 2011 and Rashtriya Swasthya Bima Yojana (RSBY) databases, along with states using databases from state-run/state-specific schemes to determine eligibility of beneficiaries and consequently approve their enrolment. In 2022, Irdai and the NHA proposed working together to develop the National Health Claims Exchange, which would serve as a digital platform to settle health claim. PMJAY could also witness uptake of ML technologies if relevant and complete claims data can be harnessed from this platform to aid in more efficient claims management.

Box 13: 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 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 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 of the country due to lack of adequate cloud computing, high speed internet and computing power (Srivastava, 2018). As discussed in section 4.2 above, physical infrastructure requirements include availability of fast and reliable networks, secure locations for data storage and adequate hardware needed to support the continuous use of these advanced ML technologies.

5.3 Strengthening workforce

We highlight in section 4.4 above, the need for governments to build technical rigor and expertise through employment of a workforce that is aware and experienced with the growing changes in the technology sector. To confidently adopt ML technologies for its operations in public health insurance, PMJAY will need to build a workforce that can support the successful application of these algorithms/models across key functional and support areas. A needs assessment on human resource requirements, in correspondence with the scope and scale of technologies chosen to be adopted, would be useful to build 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. This will also help the government reduce dependencies on the private sector and work in greater tandem with them, matching their competencies and efficiency levels. Establishing a sound balance between humans and ML technologies will aid in building greater understanding of the technologies within the public and will enable trust and acceptance.

5.4 Ensuring financial soundness

As the application of ML methods requires large financial investment, and although it may seem rewarding to tackle the most difficult problem first, it may be more sustainable and achievable if “low hanging fruit” challenges are undertaken first, before significant investments are made by governments for public use.

Improvement in patient access and health outcomes can be achieved by managing technology effectively and efficiently. Useful innovation has enabled the creation of advanced ML technologies that can aid the health-care sector beyond diagnosis and patient management. 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 sustainability of digital and ML technologies (Tromp et al., 2022).

The application of technology carries both short- and long-term consequences, for example, societal, economic and ethical, and the examination of these consequences constitutes technology assessment (TA) (Banta, 2009). This has been used to identify the desirable first-order, intended effects of technologies as well as the higher-order, unintended social, economic and environmental effects (Goodman, 2014).

In order 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). “HTA is a multidisciplinary field that addresses the health impacts of technology, considering its specific health-care context as well as available alternatives. Contextual factors addressed by HTA include economic, organizational, social, and ethical impacts. The scope and methods of HTA may be adapted to respond to the policy needs of a particular health system” (Goodman, 2014). This will assist the NHA in looking beyond a “use-case” mentality and exploring ways that fit the India 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.

5.5 Countering ethical difficulties

Presently, the Ministry of Electronics and Information Technology is responsible for securing India’s cyber space, for internet governance, and to ensure the use of ICT for inclusive growth, amongst its other key objectives[22]. India currently lacks a regulating body that oversees AI impact in the health-care sector, or health insurance in particular. The aim of such a regulating body would be to assure 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 pay for its use. Ethical implications involved in the use of AI health care include difficulties related to bias, lack of consciousness, lack of data privacy and singularity - the growth of AI intelligence beyond humans (Srivastava, 2018). Explicit national guidelines on data access and security and promoting harmonization of policies between institutions will be useful in ensuring the right kind of legislation and policy are in place to deal with ethical difficulties.

India can draw from various works undertaken on data privacy and protection in Europe. For example, the European Initiative on AI launched by the European Commission aimed at boosting the European Union’s (EU) technological and industrial capacity and AI uptake across the economy, along with preparing for socio-economic changes brought about by AI. It also focused on ensuring an appropriate ethical and legal framework, in sync with EU’s values and in line with the Charter of Fundamental Rights of the EU. The EU was aware of the importance of developing and applying AI in an appropriate framework which would promote innovation and respect their values and fundamental rights, as well as ethical principles such as accountability and transparency.[23] The General Data Protection Regulation (GDPR) has been a crucial instrument in ensuring a high standard of personal data protection, including the principles of data protection by design and by default. In case of Australia, a trust framework for the government has been drafted and proposed, aiming to help improve public confidence and trust in public institutions, policies, and services (Andrews, 2022). It has been designed specifically for the public sector and is supposed to complement principles-based frameworks like Australia’s AI Ethics Framework (Andrews, 2022).

India can identify its need and core challenges, and accordingly build guidelines and policies that assist with careful governance and regulation, to promote fair, unbiased, and transparent use of advanced technologies for the betterment of the general public. One such step in this

[24] https://www.meity.gov.in/about-meity/vision-mission

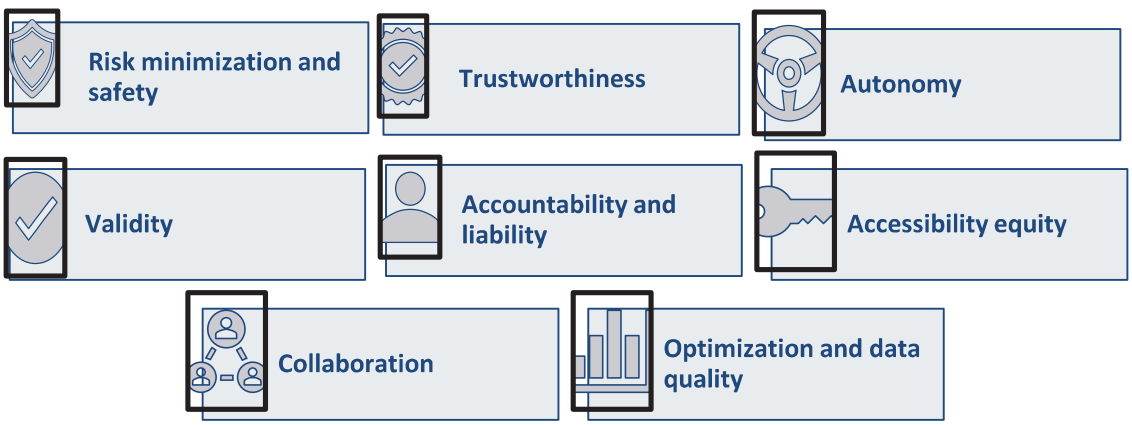
[25] Communication From the Commission to The European Parliament, The European Council, The Council, The European Economic and Social Committee And The Committee Of The Regions. Artificial Intelligence for Europe. Brussels, 25.4.2018.

direction, which has been taken by GoI, is the creation of 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).

As stated in the draft guidelines document, "The purpose of these guidelines is not to limit innovation or recommend any disease-specific diagnostic or therapeutic approach but to guide effective, yet safe development, deployment and adoption of AI based technologies in biomedical research and health-care delivery".

These guidelines highlight that AI for health, in any capacity, affects human life and can have grave implications on all aspects of patients. An ethical approach for these ML algorithms is proposed herein, which is cautious but non-obtrusive, as can be seen below in Fig. 7 below (ICMR, 2022).

Fig. 7: Ethical principles in AI for health care



Hence, what is of utmost importance is that guidelines like these, drafted especially with India context, be put into action at the earliest to guide all the stakeholders in the development and deployment of responsible and reliable AI for health.

5.6 Considering a maturity model approach

As an initial step, the aim should be to achieve "low hanging fruits" challenges before expanding application of ML more widely. It is important to distinguish between the most desired and the most feasible objectives possible to be achieved following the application of ML technologies in any given area. In case of public health insurance, various uses, current and potential, have been identified and discussed in section 3 above. It is however crucial to recognise that while some areas require more long-term investments, in some areas current systems could be strengthened to perform better or simpler technologies could be adopted sooner to yield better outcomes faster. The most crucial step is first to identify which area needs the most of ML applications, and why and how that can be applied. As implementing such methods involve big investments, conducting a cost-benefit analysis on pilot basis would be beneficial to first understand the impact corresponding to the resource required. If found resource efficient and effective to achieve goals, this pilot exercise would also guide in developing the longer-term roadmap.

One such area, as highlighted in our expert interviews, is assessing claims, and identifying fraud, with an aim to deter fraudulent and abusive activities. As expressed in an expert interview, identifying, and eliminating as little as ~5% of fraud cases in India can help the current scenario tremendously. Use of rule-based alerts/algorithms and pattern matching to catch duplicate claims were also discussed in our expert interviews and the need to identify unneeded lab tests/diagnostics tests (for example, x-rays, CAT scan, MRIs) was also stressed upon. The latter could also help with insurance claims since unwarranted charges could be kept at bay and claim denials could also be reduced.

A framework subjected to Anti-Fraud Guidelines 2018 is present in Ayushman Bharat, and the government has used AI to place an extra layer of protection therein to monitor trends formulate standard treatment protocols to check the irregularities caused due to over-billing or over charging, over testing, wrong beneficiary information and abuse in referral mechanism (Srivastava, 2018). As envisaged already under PMJAY, a “man-machine” model can be built using appropriate ML technology that can generate triggers for suspicious transactions and entities, and also be used to close investigations of such transactions (NHA, 2021).

However, before expanding the application of ML methods, the roadmap can be built based on a “maturity model” (MM) approach. MM is a conceptual framework, which follows a sequential expansion based on a certain required maturity level across few business domains (Tarhan et al., 2020). The basic approach is based on an evolutionary pathway to achieve desired outcomes.

In summary, the application of ML methods with respect to PMJAY can start with small application, identified as a domain with high priority, on pilot basis. Once, the desired results are achieved (using cycles of learnings and course-correction), subject to a rigorous impact and cost-benefit analysis and the model “matures” for that stage, it can be expanded horizontally and vertically.

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Annexure A: List of key words (indicative)

Functional areas

"Eligibility + beneficiaries"; "Beneficiary + database"; "Enrolment + beneficiaries"; "Raise or reconcile"; "Capitation + fees"; "Generate +claim"; "Raise + claim"; "Reconcile + reimbursement"; "Pay+ insurance + providers "; "Preauthorize + claim"; "Adjudicate+ claim"; "Maintain +claims +database"; "Beneficiary + communication"; "Beneficiary +complaints +management"; "Grievance+ redressal."

Support systems

"Fraud + management"; "Claims+ risk+ management"; "Facility+ accreditation"; "Provider+ accreditation"; "Provider+ profiling"; "Legislative + compliance"; "Patient + safety"; "Quality + of + care"; "Value+ based+ care."

Health insurance

"Health + care+ cost"; "Heath + care+ finance"; "Health+ care+ financing"; "Health + insurance"; "Insurance+ scheme"; "Public+ health+ insurance"; "Out+ of+ pocket + expenditure"; "Health+ care+ spending "; "Insurance+ claim'; "Health+ insurance+ claims"; "Private + health + insurance"; "Health + insurance+ market"; "Health+ system+ strengthening "; "Health+ service+ research"; "Risk+ adjustment"; "Patient+ cost"; "Universal + health+ coverage"; "Health+ care+ data"

Geography

"Developed+ country"; "Developing + country"; "India or LMIC"

Others

"Operational+ efficiency"; "Artificial + intelligence"; "Machine + learning"; "Supervised + learning"; "Unsupervised + learning"; "Big + data"; "Structured+ data"; "Unstructured + data"; "Neural+ network"; "Deep + learning"; "Natural+ language+ processing "; "Computational+ intelligence"; "Digital+ interventions"; "AI+ procurement"; "Algorithms / algorithm + bias"; "Health+ technology + assessment"; "Predictive + analytics"

Annexure B: Semi structured interview guide

1. **General Information**

Name of Expert:
Title / Position:
Associated organisation/institution:
Time interview started:
Time interview ended:
Name of interviewer:

2. **Introduce the project and explain briefly purpose of the interview.**

Note for interviewer**:** Kindly ensure that the respondent understands that this global review will not be covering/focusing on the following: (i) opportunities and challenges of AI/ML as they pertain to healthcare delivery in general and particularly w.r.t diagnostics; and (ii) formulating recommendations on regulatory issues that might relate to the use of AI/ML in healthcare financing.

3. **Obtain informed consent and begin the interview.**

Introduction: Tell us about yourself

- Could you please share how you came about your current role as XX in YY, and what your work overall constitutes?

On healthcare financing/health insurance

- Can you please tell us about your experience working in health care financing?
- Does, or has, your work included a focus on universal health coverage?
- Have you worked with publicly and/or privately funded health insurance schemes?
- If yes, what are/were these insurance schemes? What countries do/did they cover?

On AI/ML technology

- Have you worked with AI and/or ML techniques/methods in your everyday work?
    - Aim to identify if the respondent has applied these techniques in their work (for example, a data scientist) or are they someone who has managed such applications.
- If yes, how long have you been associated with this technology and in what capacity?
- What has your overall experience in this emerging field been like so far?
- How do you view the congruence of technology and health in these changing times, basis your personal and/or professional understanding/experience?

Discussing AI, ML in healthcare financing

- In your best words, describe what you consider AI and/or ML to comprise.
    - Inquire about concepts like big data, data mining and analysis, algorithms, etc., and

what the respondent categorizes as AI and/or ML, and why.
    - Discuss how the definition of AI/ML have evolved over the last decade or so, in their opinion.
- What are the types of AI and ML techniques/methods you are most familiar with, particularly in health financing?
- What are the types of AI and ML techniques/methods, according to you, currently most prevalent in the healthcare industry and publicly funded systems, particularly in health financing?
- If you were to identify one approach/application of AI/ML w.r.t health insurance schemes that you consider most promising, what would that be?
    - Inquire about areas under health insurance schemes where application has been most witnessed or is being most explored, for example, strategic purchasing, identification of beneficiaries, claims adjustment.
    - Inquire about gaps w.r.t unexplored areas under health insurance schemes.
    - Inquire about stakeholders involved from governments, beneficiaries/citizens, Third Party Administrators (TPAs) to health care providers/professionals and their role.
- What according to you is the potential of this application w.r.t publicly funded health insurance schemes in particular?

Successes and challenges
- Can AI and ML techniques/methods be considered impactful on healthcare financing for universal health coverage (UHC)[24]?
- If yes, what according to you is the nature and scope of their impact on healthcare financing for universal health coverage?
    - Discuss effects on efficiency w.r.t health financing functions [25] being performed quickly, more accurately or less expensively.
    - Discuss benefits identified/positive results shared and effectiveness in countering disruptions / inadequacies
    - Discuss implementation challenges w.r.t application or adoption.
    - Discuss benefits w.r.t beneficiaries and health care providers/professionals; also, TPAs.
- What were/are challenges you have faced in your line of work in this sector so far? What kind of mitigation strategies have bee/can be adopted to combat them?
- In your opinion, what are some enabling factors in institutionalizing the use of AI/ ML in public health financing?

Ethics, regulation, and governance of AI in health care
- What are some emerging trends in regulation and governance of AI/ML or digital health more broadly within country health systems?
- What is needed in the institutionalization of the use of AI and ML in health care financing (data processing, HR, governance arrangements)?
- How have issues w.r.t data privacy been dealt with, so far, in your opinion?

[26] Universal health coverage means that all people have access to the health services they need, when and where they need them, without financial hardship. It includes the full range of essential health services, from health promotion to prevention, treatment, rehabilitation, and palliative care. (WHO). https://www.who.int/health-topics/universal-health-coverage#tab=tab_1

[27] Core value adding processes of a publicly funded health insurance scheme: Develop, maintain and price benefit package, Establish and maintain provider/hospital network; Eligibility review and enrol beneficiary; Maintain beneficiary membership database; Link beneficiary with facility; Pre-authorise treatment; Receive and adjudicate claim, Update beneficiary database; Pay provider/refund member; Reconcile claims, risk equalisation, and forecast expenditure; Provide beneficiary customer care

- How has data-driven bias affected the development and uptake of AI in the health care sector?
- In your opinion, what are the potential barriers in institutionalizing the use of AI/ ML in public health financing?
- How can the need for a continuous flow of data be maintained?
- In your opinion, how has access to and ownership of data, that is driving AI/ML techniques globally, being accounted for and/or regulated? What are potential ethical issues that may arise/or have arisen in the past?

Resource requirements – physical/financial/human

- In your opinion, what kind of infrastructural support does the use of AI/ML in healthcare financing/healthcare sector need?
    - Focus on specific infrastructure requirement w.r.t health insurance
- In your opinion, how can adequate resource allocation take place w.r.t use of AI/ML in healthcare financing?
- In your opinion, does a skills differential exist between LMIC and OECD countries? If yes, how can this be problematic? How can this gap be bridged?

Way forward

- How do you think the role of AI, ML can be expanded going forward?
- What are some anticipated global challenges in this emerging sector?
- What can developing countries learn from developed countries in this area?

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Notes