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AI and healthcare financial management (HFM) towards sustainable development

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AI and healthcare financial management (HFM) towards sustainable development

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Editorial: AI and Healthcare Financial Management (HFM) towards sustainable development

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Editorial on the Research Topic
AI and Healthcare Financial Management (HFM) towards sustainable development

The World Health Organization's (WHO) Global Health Security (GHS) index of 40.2/100 indicates that almost every country has critical healthcare gaps in prevention, detection, reporting, rapid response, the capacity of the healthcare system, compliance with international standards, risk situations, and health financing for sustainable development. The amount of money people spend on healthcare out-of-pocket depends on how serious their disease is and how much money they make as a family. Healthcare expenses paid out-of-pocket are closely correlated with household income (including transfers), savings, or loans. If the household pays, such expenditure results in healthcare inequities.

With this background, the Research Topic, "*AI and healthcare financial management towards sustainable development*," has been put forward in Frontiers in Artificial Intelligence to develop solutions to minimize the gaps by soliciting detailed manuscripts from the multi-disciplinary research community. Over the last 9 months, 15 manuscripts were submitted by diverse scholars and 10 articles were accepted for publication after rigorous peer review. Of the 10, four were research-based, four were conceptual, and two were review articles. This editorial note summarizes how each article helped to achieve the scope of the special topic and in turn, the United Nation's (UN) Sustainable Development Goal 3 (SDG-3).

A hybrid-based knowledge model for recording, storing, indexing, and querying African traditional herbal medicine, ATHMed, is investigated in the study (Devine et al.). The authors extract ATHMed data using ML and ontology. The framework employed a multi-word search pattern and a corpus that has been semantically tagged. The authors gather initial data and develop an ML technique for processing, storage, and retrieval to minimize SDG-3 gaps in the African community.

In the study (Manoj Kumar, Sastry et al.), two sub-indicators of SDG 3.8, access to high-quality (SDG 3.8.1) and affordable healthcare (SDG 3.8.2) are examined for ensuring universal health care (UHC) in three economic blocks: the developing Gulf Cooperation Council (GCC), developing countries Brazil, Russia, India, China, and South Africa (BRICS), and the developed countries of Australia, the UK, and the USA. The authors use the WHO Global Health Indicator database and UHC periodical surveys and find that the ML Random Forest Tree method is superior to the OLS model in terms of lower RMSE. ML Random Forest Tree predicts that private health expenditure, out-of-pocket spending per capita in US dollars, and voluntary health insurance as a percentage of current health expenditure, impact UHC. The study has ramifications for financial and health policies including low-cost social health insurance for the underprivileged in the developing economic blocks.

The study (Rao, Manoj Kumar et al.) uses weekly time-series data from January 2003 to December 2020 to predict first-time investor sentiments (IS) to attract investments for the growth of the health sectors of India, mainland China, and the UAE. An ANN design better mimicked investor cognitive behavior than the logistic model. Current health spending as a proportion of GDP, the USA IS predictor—spread, and GDP—annual growth percent factors influenced emerging nations' IS behavior. The study findings imply that these emerging nations' healthcare sectors have significant investment opportunities for achieving the 2030 SDG-3 and SDG-8 targets.

The scope of the financial market, which produces around 1.145 trillion megabytes (MB) of data per day (including health data), is examined in the article (Abdul Razak et al.). Massive data system analysis improved family living standards, stabilized societal activities, and enhanced environmental criteria for sustainable development. The article uses the sliding window approach and random forest algorithm to stabilize the behavior. The proposed approach provides promising results in terms of accuracy in detecting concept drift over the state of existing drift detection methods like one-class drift detection (OCDD), adaptive windowing (ADWIN), and the Page-Hinckley test.

The article (Atalla et al.) suggests autonomous intelligent healthcare prevention tools to assist multimorbid elderly patients in monitoring, anticipating, and responding to health status by alerting doctors and patients to lower unexpected health complications in real-time.

The UN's 2030 SDGs, India's National Health Policy, and the UAE's Ministry of Health Policy challenges, all call for a digital health ecosystem as outlined in the article (Manoj Kumar, Patil et al.). SDG Goal 1 and its connected purposes are the basis for virtual consultations, telemedicine, virtual storage, and virtual communities. SDGs 2 and 3 monitor and analyze PHC and POC data. In rural, urban, and remote populations of the UAE and India, the concept augments the PHC system with ICT-based interventions, to improve patient health outcomes.

The article (Manoj Kumar, Atalla et al.) finds that deep learning approaches are a good, practical, and economical diagnostic tool for COVID-19. This research shows the least expensive and most reliable imaging strategy for predicting infections, by comparing COVID-19 detection methods, which have implications for reducing health insurance costs.

The article (von Ulmenstein et al.) conceptualizes a novel AI model to access medical information that threatens to exacerbate adverse selection in the health insurance market, by conducting an interdisciplinary conceptual analysis to examine how this risk could be mitigated, taking into account legal, ethical, and economic considerations. The authors propose that these health hazards cannot be disregarded in future medical applications of AI forecasting and must be handled structurally.

The study (Abdul Razak and Nirmala) conceptualizes many forms of concept drift problems in healthcare data streams and summarizes the available statistics and ML methodologies for addressing concept drift. The authors also emphasize the use of deep learning algorithms for concept drift identification and provide a summary of the various healthcare datasets utilized for concept drift detection in the categorization of data streams.

The authors of the article (Rao, Sastry et al.) study the role of AI-based cost optimization in India's universal colorectal carcinoma (CRC) prevention campaigns. AI-based detection tools and CADx systems are the way forward in CRC prevention. They reduce CRC and ADR and India's cost-effectiveness is shown to have improved. AI may change CRC screening by determining the colonoscopy monitoring interval based on morphological and clinical factors. This might help reallocate Resources and avoid repeat treatments for low-risk patients. This strategy might save money without compromising pharmaceutical safety or effectiveness. AI-based polyp detection and characterization may enhance CRC prevention.

In conclusion, the authors have done a pretty good job of addressing the objectives of the Research Topic. A sincere thank to each one of them for their contribution.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Toward a Knowledge-Based System for African Traditional Herbal Medicine: A Design Science Research Approach

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This article illustrates a design approach for capturing, storing, indexing, and search of African traditional herbal medicine (ATHMed) framed on a hybrid-based knowledge model for efficient preservation and retrieval. By the hybrid approach, the framework was developed to include both the use of machine learning and ontology-based techniques. The search pattern considers ontology design and machine learning techniques for extracting ATHMed data. The framework operates on a semantically annotated corpus and delivers a contextual and multi-word search pattern against its knowledge base. In line with design science research, preliminary data were collected in this study, and a proposed strategy was developed toward processing, storing and retrieving data. While reviewing literature and interview data to reflect on the existing challenges, these findings suggest the need for a system with the capability of retrieving and archiving ATHMed in Ghana. This study contributes to SDG 3 by providing a model and conceptualizing the implementation of ATHMed. We, therefore, envision that the framework will be adopted by relevant stakeholders for the implementation of efficient systems for archival and retrieval of ATHMed.

Keywords: knowledge base, ontology, traditional herbal medicine, design science research, machine learning

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INTRODUCTION

Countries worldwide are striving to promote good health and wellbeing for their citizens. Achieving universal healthcare by meeting United Nations' (UN) Sustainable Development Goal (SDG) 3 is the focus of many countries. The SDGs provide an ambitious and comprehensive plan of action for ending the injustices that underpin poor health and development outcomes (SDGF, 2020). It also seek to achieve universal health coverage and provide access to safe and effective medicines and vaccines for all (SDGF, 2020). The African continent is undoubtedly one of the poorest continents with poor health conditions, though it can boost of rich natural resources. It is therefore imperative for the continent to harness its own potential and available resources, including herbal medicine, to realize good health outcomes instead of relying on the western countries for solutions. This study contributes to the realization of the SDG 3 by developing a computational framework for the effective and efficient implementation of ATHMed.

In the spirit of sustainability and standardization, WHO (2019) has thrown the challenge to the global community to build knowledge bases for the management of traditional herbal medicine in its Traditional Medicine Strategy (WHA62.13) 2014–2023 (WHO, 2019). Historically, several approaches have been adopted to assist in properly and sustainably securing, in addition, to efficiently sharing knowledge. Current practices and the nature of the challenges presented point toward employing knowledge management approaches which largely is dominated by computer-based solutions. Therefore, a computing-focused solution is advocated to be most suited to answer this call by adopting sustainable, progressive, and novel approaches to help safeguard ATHMed knowledge (Devine et al., 2019). The value of computer-based approaches extends through history as the impact leads to sustainability. This article discusses a hybrid approach involving the use of machine learning and ontology approaches for preservation and retrieval of THMed knowledge. It further discusses preliminary work on data collection and how it influences the design of the proposed ATHMed KB framework. Additionally, this article illustrates search approaches influenced by natural language processing techniques that can be adopted toward the preservation and retrieval of ATHMed knowledge acquired from "deep smart" knowledge bearers using computing strategies. This is aimed at presenting explicit, well-articulated ATHMed knowledge for formal training and research in Medical Institutions of Higher Learning while promoting use in the herbal business industry. Adopting a design science research allows a preliminary understanding of the herbal medicine ecosystem. Therefore, data was elicited from stakeholders of ATHMed.

For many centuries, diverse methods have been applied in different cultures to provide healthcare. Popular amongst these forms of practice in Ghana is the orthodox and traditional herbal treatments. Traditional herbal medicine can help many countries to achieve SDG3, especially in the developing context. Traditional herbal medicine was the first method of healthcare practice in Ghana (Appiah et al., 2019). Traditional herbal medicine (THMed) with other complementary and alternative healthcare practices are widely prevalent in many regions in Africa (James et al., 2018; WHO, 2019). The 2019 World Health Organization (WHO) report on traditional and complementary medicine indicates a growing interest in the area, which is undergoing revival, "given the unique health challenges of the twenty-first century" (WHO, 2019, p. 5). Interestingly, the WHO report also shows many countries have formulated national policies and regulation, and developed programmes covering herbal medicine, thus interest in this healthcare alternative is growing. This prominence has encouraged WHO and other multilateral organizations to play "key roles in supporting capacity development in the traditional medicine sector, including the development of local manufacturing" (WHO, 2021, para. 9), leading to WHO, the African Union Commission and Africa CDC jointly launching the Regional Expert Advisory Committee on Traditional Medicine for COVID-19 Response (WHO, 2021). It is also reported that many of these herbal users are in developing countries due to the perceived potency, ease of use and low cost (James et al., 2018; Appiah et al., 2019; WHO, 2019). In Ghana, though orthodox medicine is highly patronized, it is estimated that 70% (Amoah et al., 2014) to 80–99% (WHO, 2019, p. 71) of its population are claimed to use herbal medicine to treat their ailments and complement their healthcare needs.

Reportedly, yet likely, the knowledge is habitually presented in part which in effect leads to half-baked herbal practitioners providing questionable medical care, implying medication prepared is likely not to perform what it promises, as such dangerous to the health of ATHMed patrons (Yeboah, 2000). Amoah et al. (2014) indicate that herbal practitioners often poorly communicate and hardly document their knowledge resulting in knowledge failing to be developed or maturing into an accepted treatment, practice or medication, or that knowledge is eventually lost. This approach to knowledge transfer is deemed to be tacit, as it consists of the ideas, experiences and skill set possessed by a person which is often difficult to access and transfer (Chugh, 2018, p. 2; Nonaka and Takeuchi, 1995). This tacit approach is inefficient and not appropriate for long-term preservation and use of knowledge. This probably expounds the reason for ATHMed knowledge being lost with time. There are reported instances of misinformation, misappropriation and abuse of herbal knowledge especially associated with the traditional health knowledge (Yeboah, 2000, p. 208). This raises a cause for concern due to poor ATHMed documentation. The lack of appropriate documentation for ATHMed practice involving the selection of ingredients, preparation methods, and their administration has brought the quality, efficacy, and safety of ATHMed into suspicion (Chikezie and Ojiako, 2015). Regrettably, this has formed doubt in the patronage of herbal products and medication. The relevance of knowledge preservation cannot be downplayed as it holds strategic influence on the growth, sustenance, and competitive advantage of any environment, organization, or people for that matter (Davenport and Prusak, 1998; Xue, 2017) Consequently, steps to mitigate and possibly correct the challenge bedeviling the practice of proper documentation associated with ATHMed appropriate strategies are necessary to salvage the situation. To this end, there have been many calls seeking to improve and formalize the practice of proper preparation and preservation of such practices (WHO, 2019).

LITERATURE REVIEW

Traditional Herbal Medicine in Ghana

Traditional medicine, according to WHO, involves "knowledge, skill, and practices based on the theories, beliefs, and experiences indigenous to different cultures, whether explicable or not, used in the maintenance of health as well as in the prevention, diagnosis, improvement or treatment of physical and mental illness" (WHO, 2019, 2020, p. 44). In the case of herbal medicine, it involves "herbs, herbal materials, herbal preparations and finished herbal products that contain as active ingredients parts of plants, or other plant materials, or combinations" (WHO, 2019, p. 29). Tilburt and Kaptchuk (2008) situate traditional herbal medicines to imply "naturally occurring, plant-derived substances with minimal or no industrial processing that have been used to treat illness within local or regional healing practices".

A larger proportion of herbal medicine patrons are in the rural areas (Amoah et al., 2014; James et al., 2018; Appiah et al., 2019). Research into the domain of traditional and herbal medicine has gained renewed interest (Appiah et al., 2019; WHO, 2019). However, despite its relevance, the knowledge regarding ATHMed dissemination is verbal, remains largely undocumented and poorly recorded (Chikezie and Ojiako, 2015; Boadu and Asase, 2017; Appiah et al., 2019). Furthermore, the processes of identifying, preparing and administering herbal medicine have come under critique. Cases of misapplication of medication, perceived adverse side effects, safety, efficacy, and quality, with mistrust and dosage standardization in the use of ATHMed have been cited in reports and literature (Yeboah, 2000; Chikezie and Ojiako, 2015; Boateng et al., 2016; James et al., 2018; Appiah et al., 2019). A major factor contributing to this is the poor documentation, or lack thereof, often associated with the practice of African traditional herbal medicine (Appiah et al., 2019). The knowledge bearers of herbal practices, thus the herbal medicine practitioners, often have an exclusive hold on their knowledge. In the act to protect their trade and knowledge, many ATHMed practitioners, especially in Ghana, prefer to pass on their knowledge to only their close relatives and through generations (Boadu and Asase, 2017; Appiah et al., 2019). Adekannbi et al. (2014) observe that although certain herbal practitioners are willing to part with their knowledge, they intentionally and articulately attempt to transfer their knowledge to assistants who are their close relations. This transfer is often and primarily done through observation and direct practice with little or no documentation (Boateng et al., 2016). Leisurely, the knowledge is presented orally to these ATHMed trainees, who learn by doing and are only exposed to the knowledge at the pace and wish of their trainers who are the sole bearers of the herbal knowledge (Yeboah, 2000; Adekannbi et al., 2014; Soelberg et al., 2015; Boateng et al., 2016; Maluleka and Ngulube, 2018; Appiah et al., 2019). Appiah et al. (2019) emphasize that in-depth knowledge on ATHMed is at the brink of extinction due to the predominant reliance of oral mode of transmission. Sadly, this often leads to the likelihood of such knowledge being either lost or failing to be developed over time (Amoah et al., 2014). In the case where the knowledge is not shared at all, the practitioner eventually dies with the knowledge (Appiah et al., 2019).

As widely observed in literature, there exists a number of patrons for traditional herbal medicine in Ghana (Yeboah, 2000; Boadu and Asase, 2017). The use of herbal medicine and its means of preparation have gained the attention of many stakeholders including governmental institutions, health institutions, and academia in addition to its practitioners and patrons. This is due to the patronage and role it plays in providing and supplementing healthcare needs of Ghanaians who acquire such THMed from licensed shops that sell herbal products and herbal clinics (WHO, 2019: p70). However, as earlier indicated, the practice and its products have also come into question placing doubt on ATHMed products which can also be associated with standardized practices of drug preparation and administration (Boateng et al., 2016; Boadu and Asase, 2017). This has influenced diverse approaches to protect not only the citizenry but also assist in producing practitioners who are well-trained in the area. This is effectively possible *via* the availability of knowledge that is well-defined or explicitly documented. The Government of Ghana realizing such a need has set up the Centre for Scientific Research into Plant Medicine to lead the way in the preparation and standardization of herbal medicine in Ghana (Amoah et al., 2014; Appiah et al., 2019).

In recent times, attempts have been made by Universities in Ghana to train pharmacists in the area of indigenous African herbal medicine treatment. The Kwame Nkrumah University of Science and Technology offers a degree programme in herbal medicine at the undergraduate level. Such training is in an attempt to assist in formalizing the training of professionals in herbal medicine. However, their focus has mainly been to help curb the challenge related to the Ghanaian traditional herbal medicine practitioner's accurate measurement of ingredients for drug preparation with issues on the quality. The universities also strive to provide strategies for long-term preservation, appropriate forms of administration, and administering the right dosage of such herbal drugs. For instance, the University of Ghana in 2016 organized a 2-day face-to-face training programme for manufacturers of herbal products/food supplements, focusing on the improvement of safety and efficacy, evaluation of raw materials, toxicological assessment, quality, and standardization in Ghana. These interventions seek to harness the potential of herbal medicine, providing orthodox and scientific approaches to standardizing and safeguarding the knowledge associated with it and the practices in applying medication. This attempt also assists in documenting and preserving practices and medications associated with African traditional herbal medicines which hitherto was in the domain of the practitioner. Failure to undertake such interventions would, in the end, lead to loss of these indigenous yet efficient medicinal approaches (Boadu and Asase, 2017). It is for this call that we proposed this framework, targeted at providing a knowledge-based system for the efficient, sustainable approach to safeguarding ATHMed knowledge to a more explicit form.

Knowledge Management Approaches

Throughout history, attempts and varying approaches have been developed and implemented to safeguard, as well as disseminate knowledge. This is to ensure posterity and present benefit from works, acts, processes, information and all relevant data that will help improve or maintain personal to organizational and societal development needs. These views are critical and relevant toward the debate on the predominantly inefficient ATHMed knowledge preservation practices as revealed in literature (Yeboah, 2000; Adekannbi et al., 2014; Maluleka and Ngulube, 2018). Knowledge, as an asset in whichever form, is regarded as key to any organization's present and future growth, and competitive advantage especially in the 21st century (Xue, 2017). Different views have been suggested (Bolisani and Bratianu, 2018) on what "knowledge" is, though many of these definitions still point toward Plato's postulation of knowledge as being "justified true belief" (Nonaka and Takeuchi, 1995). Knowledge, however, can be classically expressed in contemporary times as encompassing a flexible fusion of expert opinion, context-based information, personal exposure, practices and thoughts or reasoned actions, values and norms, and procedures. It is often viewed as inherent and defined by the people who own or use it (knowledge workers) (Davenport and Prusak, 1998), as in the case of many THMed practitioners. This suggests that knowledge can be explicit or tacit in nature (Nonaka and Von Krogh, 2009). By implication, the context and timing, depth and/or coverage and volume may contribute to its value and relevance to any individual or organization's actions and decision-making processes (Meacham, 1983; Kakabadse and Kakabadse, 2001). In this light, it is imperative that, knowledge, in whichever form (explicit or tacit), must be carefully managed, safeguarded and disseminated, thus yielding the relevance of knowledge management.

Knowledge Management (KM) has evolved since its inception as a concept in the 1990s into a full academic discipline, taking different dimensions of classification and study (Xu et al., 2008; Girard and Girard, 2015). Advancement in technology, with the coming of age of computing, has greatly impacted on KM practices. According to Girard and Girard (2015) the "classic and most cited" epistemological attempts in defining KM could be attributed to Davenport and Prusak (1998), and O'Dell and Grayson (1998). In attempting to define KM, many academicians and practitioners, from varying points of view, often leaned toward their disciplines and domains of practice or research. From their observations, Girard and Girard (2015) suggest a definition for KM based on 100 sampled definitions spanning various disciplines from extant literature, having regular occurring words including "use, create, share, knowledge, process, organization, and information". This research, from the foundational definitions, views knowledge management to be an approach, discipline or mechanism encompassing activities or processes that involve the efficient, systematic, meticulous acquisition of knowledge, accessing, evaluating, dissemination, maintenance and management of knowledge, be it tacit or explicit to the benefit of individuals, groups or organizations (O'Dell and Grayson, 1998; Antoniou et al., 2012; Girard and Girard, 2015).

Research has been intensified in the area with new disciplines interacting with the KM concept to provide an encompassing approach to harness and efficiently manage and disseminate such crucial knowledge, especially for mission-critical tasks or projects within organizations (Davenport and Prusak, 1998). Advancement in technology, with the coming of age of computing, has greatly impacted on KM practices, especially in preservation and retrieval. Consequently, various techniques, strategies and concepts in areas such as Artificial intelligence, machine learning, analytics, data mining, amongst others, have been adopted and incorporated in KM and KM Systems (Chen et al., 2005). The approach of preserving knowledge through KB with ontologies has helped reshape the focus of the domain, especially with this ubiquitously rapid growth of knowledge existing on the web and in organizations (El Morr and Subercaze, 2010). KM also has extended from focusing solely on organizational knowledge to personal knowledge of individuals (Wright, 2005) within the organization, seeking to maximize their productivity (Cheong and Tsui, 2010), consciously or unconsciously. As such, a look into prevailing computing approaches employed currently in KM is necessary and the extent to which it applies to THMed.

Mazour (2006, p. 2) expounds knowledge preservation as "a process for maintaining knowledge important to an organization's mission that stores knowledge/information over time and provides the possibility of recall for the future". This suggests the need for consistent and meticulous efforts in harnessing and documenting such critical knowledge assets. This can be achieved using information technology, thus computer-based solutions, as these are more sustainable and effective toward formalizing and explicit preservation of knowledge than verbal, oral and face-to-face approaches (Panahi et al., 2012; Ashkenas, 2013). Efficient retrieval and dissemination of knowledge, especially tacit knowledge, is heavily influenced by proficient knowledge preservation, which is vital and inevitable (Sarkiunaite and Kriksciuniene, 2005). KP processes encompass three stages involving the ability to select, store, and actualize (Probst et al., 2006) knowledge. Information technology tools identified to facilitate the KP processes are commonly associated with capturing and sharing systems (Davidavičiene and Raudeliuniene, 2010), in consequence, are focused on preservation and retrieval which involves propagation. As a result, this article focuses on the preservation and retrieval of knowledge relating to codification, representation and storage of knowledge (Antonova et al., 2006) based on prior studies to advance the need and strategy for an ATHMed KB implementation.

Extant literature in KB development indicates focus toward intuitive, robust, platform-independent, metadata dependent, semantically driven, contextual domain-based knowledge modeling, reasoning, preservation, and extraction systems. Evidenced from literature, the adoption of machine learning and ontology-based techniques with their supporting technologies were found to be recurring in diverse, multidisciplinary fields including THMed for KB and thus KB system development (Li et al., 2003; Tomai and Spanaki, 2005; Lin et al., 2013; Sanya and Shehab, 2014; Song et al., 2016; Shang et al., 2017). In their study, Song et al. (2016) explored a 3-tier system architectural framework for KB Systems management of manufacturing process knowledge. The researcher proposed an effective reusable management approach to implementing their KB system, *via* a systematic methodology for constructing the KB, indicating the key role of ontology development through an iterative process. In a related study, Shang et al. (2017), by employing a vulnerability-centric ontology-based KB framework strategy, cyber security knowledge existing in some independent KBs and the internet, in text form, can be efficiently integrated, enabling the extraction of cyber security knowledge with the use of both rule-based and machine learning information extraction techniques. This indicates that current research into KB development should be seen pointing toward the inclusion of machine learning and ontology-based technologies.

Machine Learning Approaches

Machine Learning (ML) is one of the fastest growing fields in computer science and has been applied diversely (Shalev-Shwartz and Ben-David, 2014). Since the term Machine learning was coined by Arthur L. Samuel, a number of definitions have been given. Shalev-Shwartz and Ben-David (2014) define machine learning as "automated detection of meaningful patterns in data". Machine learning involves the use of statistical-computational methods to enable a machine (thus computing system) to learn, focused on improving their performance based on experience obtained from some tasks tackled without being explicitly programmed to do so (Mitchell, 2006). Machine learning application and research in both academia and industry, as seen with evidence-based decision-making in areas including healthcare, education, business, etc. (Jordan and Mitchell, 2015), has generated immense interdisciplinary interest in the field.

Machine learning applications involve supervised and unsupervised learning, implemented through classification and clustering, respectively. This article and the proposed ATHMed framework focus on the supervised learning approach. In clustering, the classifier looks for patterns in data. Classification, as a supervised learning technique, centers on the task of learning a function that maps an input (x) to an output (Y) based on input-output pairs (x_i, y_i). Classification makes use of the initial data collected to train a machine learning algorithm (classifier) to predict unseen data. Classification involves training and prediction. At the training stage, the labeled data is classified into two forms being, training data, and testing data. With machine learning classification, the initial stages require labeling/tagging of sample (training) data, thus n-dimensional vectors that have class association labeling. The sample or input data can be labeled *manually* (by a human expert of a specific domain), *automatically* (using software with natural language capabilities) and *semi-automatically* (mixture of an expert and software) (Kolog et al., 2018).

During training, a model for the classification process is generated. To achieve this, it is ensured that large amounts of the sample (training) data is used as input for learning to the algorithm. The training data is typically textual, and thus classification can be done at different levels, being at the word, sentence, and document levels (Kolog et al., 2019). Firstly, feature extraction of instances is performed on the training data using some technique like part-of-speech-tagging to ensure the highest quality of outcome (output) is obtained to feed the classifier. In the process, *stop words* like "*a*", "*are*", and "*the*" are removed or minimized to generate a feature. For instance, the statement "*the leaves of the neem tree are used for the treatment of fever*" will become "*leaves neem tree treatment fever*". Then lemmatization is performed to obtain the base forms of the possible lexemes in the feature leading to the "*leaf neem tree treat fever*". The resulting outcome is the model.

At the test stage, the machine learning model generated will be given data to test if it is able to appropriately deduce correctly which class the extracted feature belongs to, in essence for it to predict the right output of the data. If this is correctly achieved at a satisfactory stage, learning ceases. Mathematically, for a given input (x) and output (Y) variables, the input variable is mapped to the output variable, i.e., $Y = f(x)$. The rationale is to as accurate as possible map *via* the machine learning algorithm (model) such that for any new input data (x) the model can efficiently predict ($\geq$70% accuracy) the output variables (Y) for that data such that the error on the output predicted is minimal. The predictive ability of the classifier (algorithm), thus its quality, can be measured based on its recall, precision or f-measure. Other popular methods for measuring a classifier's quality include Cohen's Kappa scores, Receiver Operating Characteristic (ROC), among others. Several studies indicate the active adoption and integration of machine learning applications in traditional herbal medicine.

Ontology-Based Approach

Ontology is considered to have its origin from philosophy. The concept has been applied in different fields of study including computer Science (CS), specifically in the area of Artificial Intelligence (AI) concentrated in the areas of knowledge management, knowledge engineering, information retrieval, natural language processing, intelligent information integration, etc. (Studer et al., 1998; Guarino et al., 2009). In an attempt to define ontology in the context of computer science, varying definition are presented with Studer et al. (1998) postulation being widely accepted. Studer et al. (1998), based on the initial definitions of Gruber (1993) and Borst (1997), define computational ontology as "a formal, explicit specification of a shared conceptualization". They further elucidated that "a '*conceptualisation*' refers to an abstract model of some phenomenon in the world by having identified the relevant concepts of that phenomenon. '*Explicit*' means that the type of concepts used, and the constraints on their use are explicitly defined. '*Formal*' refers to the fact that the ontology should be machine readable, which excludes natural language. '*Shared*' reflects the notion that an ontology captures consensual knowledge, that is, it is not private to some individual, but accepted by a group" (Studer et al., 1998, p. 25). These views fit well with the approach and focus pursued in the proposed ATHMed framework which is approached adopting the hybrid approach (ML and ontology technologies).

Computational ontologies have been identified to be suited for contextual design and representation of dynamic reasoning knowledge (Studer et al., 1998) that requires implementation of semantic components of knowledge management. Computational ontologies enable the formal modeling of a system's structure (Guarino et al., 2009). Thus, in describing things in terms of their allotted category/class and relation within the AI domain, a pragmatic view of an ontology is the ability to represent that which exists or perceived to exist (Guarino et al., 2009). This implies that an ontology can be built or constructed about anything (entity) tangible or intangible so far as their attributes (relation, instances, axioms, etc.) can be defined. Therefore, in considering an ontological approach we seek to produce a domain model that embodies classes/categories, relations, constraints, and instances applicable to that domain. Thus, the possibility of ontologies in the construction of a KBS (Studer et al., 1998), given its application in domain knowledge representation and is also applicable in natural language processing to facilitate automatic extraction of knowledge from text.

There are different types of ontologies including domain, generic, application, representational, method, and task ontologies (Studer et al., 1998). As concerned with this study, domain ontology is deemed suitable for ATHMed since it is targeted at knowledge specific to a given domain. Again, it is observed that as knowledge within an organization (applicable to THMed) evolves into diverse knowledge elements (Studer et al., 1998), novel methods for capturing, storing, retrieving, and sharing such knowledge (especially tacit) is needed, it necessitates the adoption of ontology-based approaches. Ontology technologies have been adopted in recent times in supporting semantic representation of knowledge in software applications and web environment using authoring and rendering tools. It is on this premise, among others in extant literature, that the ontology approach is deemed suitable and relevant for the engineering, capturing, storage, and querying of THMed Knowledge. Several studies have applied machine learning or ontology in knowledge representation and extraction in diverse domains. Arji et al. (2019) identified studies that involved the use of machine learning in traditional medicine. Current literature indicates the use of ontology in KB design and has been applied to the traditional and herbal medicine domain, thus THMed, with few in the African context.

METHODOLOGY

This study adopts a design science research (DSR) process for developing a framework for the ATHMed. Design science research has largely been adopted in several disciplines, especially in the Information System domain. Horváth (2007) and Baskerville et al. (2015) provided two key mandates of DSR: (1) to utilize the gained knowledge to solve problems, create change or improve existing solutions; and (2) to generate new knowledge, insights and theoretical explanations. These mandates go to suggest that DSR strives to understand the real-world problem and find a solution to that problem (Cleven et al., 2009). The real-world problem is simulated, and solution provided in the form of artifact. Artifact development in DSR can be constructs, methods, models and instantiations. DSR recommends the inclusion of the end-users throughout the co-creation of an artifact (constructs, methods, models, and instantiations) (Hevner et al., 2004). The development of DSR artifact undergoes a design process where Hevner et al. (2004), one of the frontiers of DSR, advocated for a co-creation of an artifact with stakeholders. **Figure 1** shows a DSR framework developed by Hevner (2007). The framework, as widely been used for artifact development, is made up of three stages: *Environment*, *Design science,* and *knowledge base.* These stages are not independent but linked iteratively in cycles. These cycles, as indicated **Figure 1**, are the *relevance*, *design,* and *rigor* cycles.

The environment constitutes the understanding of the application domain, which include the people, organization and the technical systems. The goal is to formulate objectives for developing solution through design and evaluate process. The design stage involves the actual development of the artifact. However, the design stage undergoes a vertical stepwise process (Design cycle: build and evaluate). The environment and design stages iterate until a desirable outcome is attained and this constitute the relevance cycle. The artifact is expected to add knowledge to the domain for which the study was undertaken. Thus, contributing to the knowledge base largely relies on the developed artifact. The iterative process, at this stage is the rigor cycle.

This article forms part of the relevance and rigor cycles where data was collected to understand the need for the system and the framework for future implementation. The development of the framework relied heavily on the need for it (stakeholders' acceptance). In view of this, the preliminary part of exploring the environment was through data collection. Diverse stakeholders in the herbal medicinal space in Ghana were purposively selected for an interview. The selection was based on their desire to advance research and promote ATHMed. Participants were selected from the Academic institutions advancing herbal medicine, Research institutions (CSIR), Local herbal practitioners, Herbal clinics, Food and Drugs Authority (FDA) and a selection of herbal medicine users in Ghana. The study complied with ethical standards. Thus, Ethical clearance from the University of Ghana ethics board was obtained before undertaking this study. An informed consent agreement form was signed by each participant before the interviews were conducted. A total of 20 stakeholders were interviewed. The interview was semi-structured that allows the participants to express their views by responding to the questions.

ATHMED KNOWLEDGE-BASED FRAMEWORK

This study adopts Initial data collected suggests a keen interest in the development of the computational framework for proper archiving and retrieving of ATHMed. The participants recognized computational systems for ATHMed as a way of contributing to practical knowledge sharing, socio-cultural sustainability concerns and healthcare delivery and accessibility issues especially to patrons and researchers in the domain. On the question of how herbal medicine practitioners are regulated in Ghana, one of the participants blamed the government for negligence in the influx of fake herbal medicine and practitioners in Ghana. One of the participants said:

> *"I think the government is not doing enough to check the herbs and the herbal clinics in the country, every day and day out people bring new herbs and just go to the street to sell to the poor Ghanaian. Our country is been poisoned by these acts."*

Nevertheless, the participants expressed their concerns about the rate at which herbal clinics and herbal practitioners are springing up without proper checks and documentation. We asked a question on their perception regarding a national database for archiving and retrieving traditional herbal medicine. Though the participants did not put the entire blame on the FDA, they rather believe that computational means to help curb the menace of fake herbal medicine is the way to go. One of the participants expressed that:

> "*Taken the step to use a more sophisticated technique to help preserve the knowledge in the herbal medicine is the way to go.*

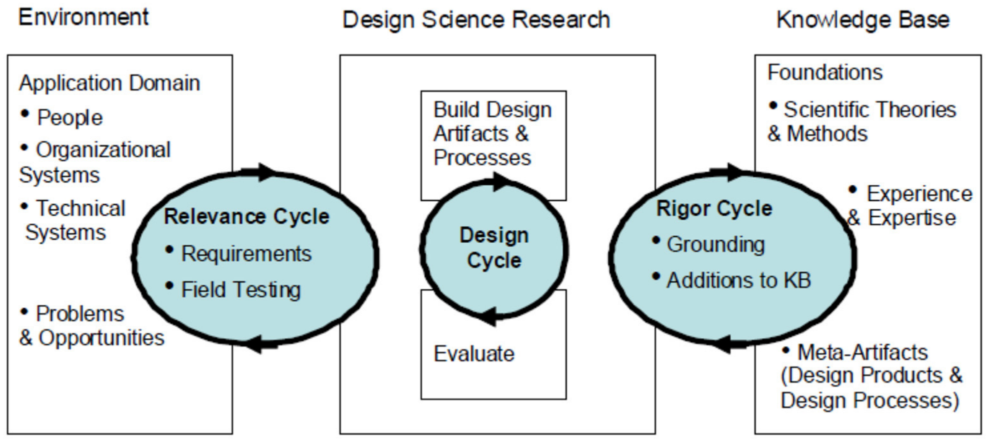

FIGURE 1 | Design science research process (Adopted from Hevner, 2007).

In fact, I don't entirely blame the authorities who mandated to check fake herbs in the market but making people aware through whatever means will automatically reduce the menace of fake herbs in the system"

Inthe interview, asked whether there is existing database in pace for archiving herbal medicine. We found out that computational systems are available in specific places, but they are not integrated. These systems are built based on the traditional database system with simple query techniques. One of the participants agreed on the relevance of the development of knowledge-based system.

"This will be a game changer. I think this will make a work flexible if a knowledge system can be developed to achieve and even help predict what herb to use for a particular ailment"

On the question of whether the participants will be willing to participate, in terms of building the knowledge-based system, the responses were positive. However, they cautioned that some of the herbs are fake and do not treat the ailment that it has been purported to treat. They, however, recommended for thorough validation with the FDA, an authority mandated to validate drugs before it is put to the market. In future, the various stakeholders will be consulted for practically implementing the framework.

The ATHMed framework, as proposed by Devine et al. (2019), is presented as a knowledge-based system composed of three (3) main layers: *Data*, *Logic,* and *Presentation Layers*, and their associated components. As shown in **Figure 2**, the framework encompasses data layer, logic layer and application layer. The data layer handles capturing, and storage of the knowledge obtained from the domain experts *via* a data acquisition sub-component and knowledge base. The middle layer—logical layer—embodies the logic that performs reasoning capabilities such as inference and deduction, and extractions of data/information/knowledge based on queries (requests) received *via* the information extraction component. The information extraction component's function is implemented through two sub-components, thus a semantic reasoner and machine learning extractor. The third layer, the presentation layer, presents a means *via* a graphical interface for users to run or pass queries in natural language syntax against the knowledge base to retrieve relevant information on ATHMed. The rationale for the segmentation of the KB framework, is to achieve conformance with current KBS design and, also enable modularity and precision in delivery of a reliable system, serviceable in an integrated, adaptive and platform independent setting, while harnessing the hybrid capabilities (machine learning and ontology specifications) discussed (Devine et al., 2019). This approach conforms to the current software design approaches that seek to adapt an object-oriented focus and is appropriate for reliability, reusability, maintainability and sustainability of semantically focused software design.

Data Pre-processing

As earlier mentioned in section Conceptualizing the Implementation of ATHMed, the data, captured at data layer stage required for the construction of the KB is to be obtained from the stakeholders which is in agreement with principles for deriving domain knowledge (Studer et al., 1998; Guarino et al., 2009). Since ontologies are focused on building consensus toward a domain knowledge (Studer et al., 1998; Guarino et al., 2009), it is necessary that stakeholders of that domain take critical interest and participate in the building or construction of the knowledge being engineered. As such constant engagement with stakeholders (who are the knowledge bearers) in the process from the information elicitation stage to the building of the final ontology is required. In addition, literature in the domain (which provide explicit knowledge) is also relevant (Boadu and Asase, 2017; Appiah et al., 2019). The initial data (stakeholder knowledge) and relevant information obtained from literature shall be used to build a corpus to train the machine learning algorithm, in hope of obtaining a robust model. **Figure 3** shows the data sources for the intended ATHMed domain which include domain experts from academia, research institutions and knowledge from practitioners would be used to build the corpus. This will require preprocessing

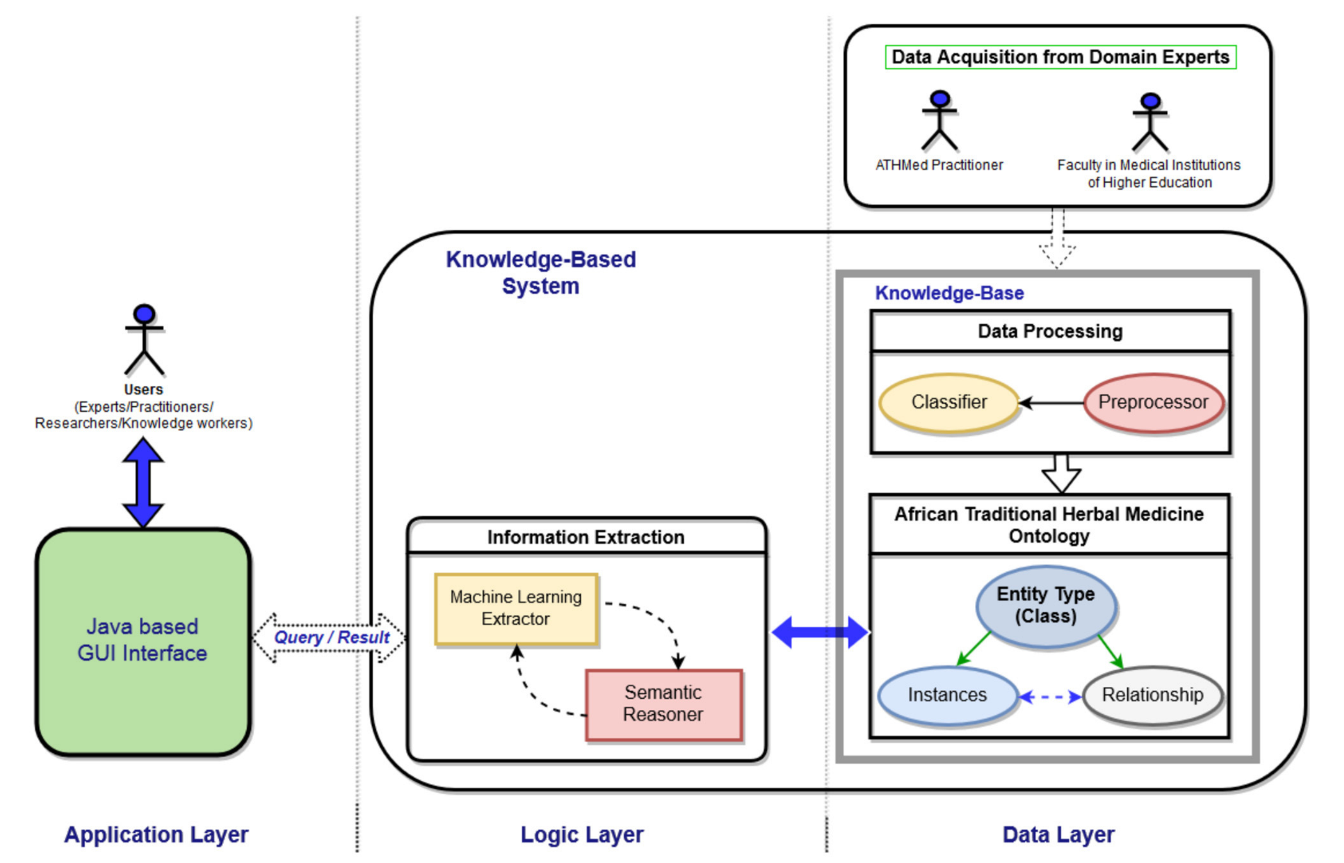

FIGURE 2 | Proposed Knowledge-based Design framework for African traditional herbal medicine (Devine et al., 2019).

of the data (unstructured) obtained from the stakeholders for easy annotation.

Preprocessing involves cleaning and conversion of unstructured data into some structured form, reprocessed and then extraction of features where required. This processing is based on the elements relevant for ingredient selection and processing, mode of preparation and administration methods. Through expert domain (academia, research institutions and registered herbal clinics) annotation, a predefine annotation scheme for the ATHMed data will be performed. This will enable the attainment of a good agreement score on what element goes where, to obtain a correctly annotated data for training the machine learning classifier as indicated in **Figure 2**. The classification process is expected to lead to each data value (or key words) being tagged to allow efficient association of terms and concepts, *via* part-of-speech-tagging (POST) through lemmatization. The processed data, appropriately labeled/tagged will then be stored into the knowledge base considering possible association of data elements, corresponding with the ontology design adopted. By this a reliable level of accuracy in the anticipated prediction and association of data to label is provided as seen in **Figure 4**. This would include feature extraction and morphological analysis through POST based on some standard medicine preparation template.

Considering the diverse nature of plant/herb types and ingredients, preparatory methods, and administration procedures and the required feature extraction through natural language processing techniques (POST), we suggest an n-gram approach be used. This implies features may be in the form of a unigram, bigram, etc. to aid in storage and retrieval of multiword based expressions and search. The choice of machine learning algorithm to be used in implementing the classifier would require testing several algorithms possibly *via* a machine learning software (e.g., WEKA). Literature indicates that different algorithms have been applied in THMed (Arji et al., 2019) and medical domain (Shang et al., 2017) with varying rates of success. Essential to the machine learning techniques is the indexing approach selected to effluence the storage and retrieval of knowledge (data) into the KB, therefore aligned to the ontology-based KB design proposed.

ATHMed Ontology Model

The ontology, the ATHMed Ontology model, is to capture all the knowledge into a structured, well-defined form. The ontology approach (computational ontologies) is being adopted to enable the knowledge base possess semantic, extensible and reusable capabilities. The ontology considers the appropriate categorization of classes, anticipated instances, interrelationships

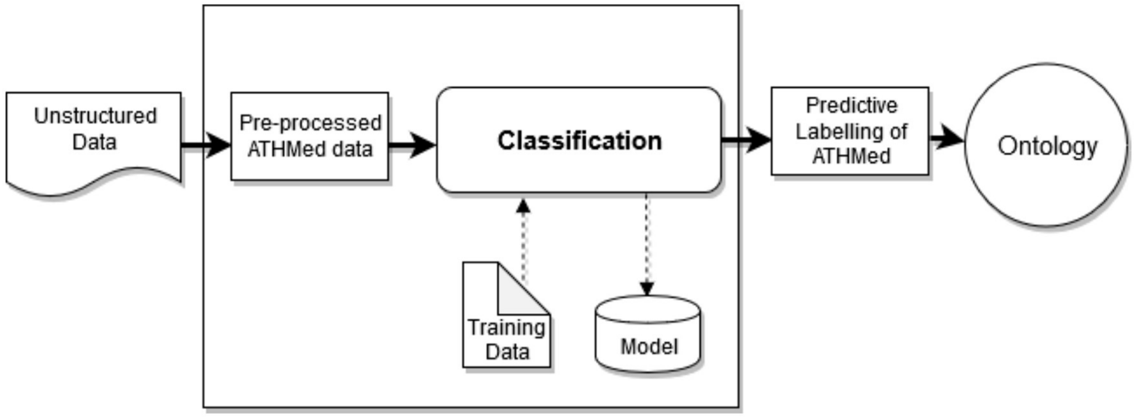

FIGURE 4 | ATHMed classification process.

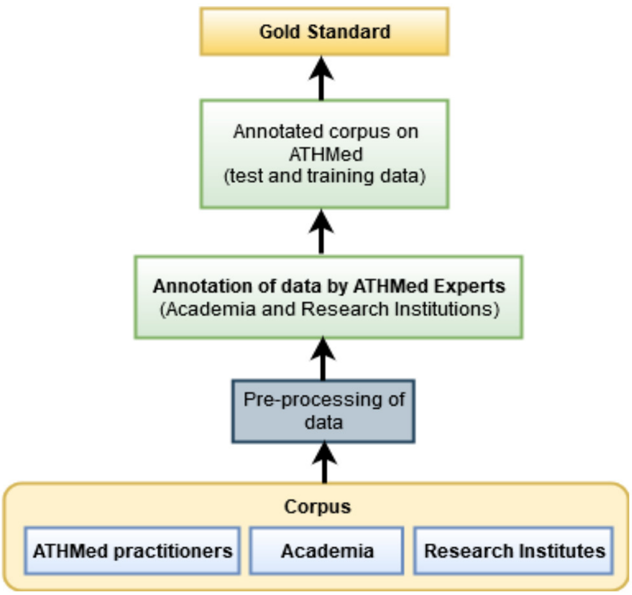

FIGURE 3 | Data sources, preprocessing, and annotation process for ATHMed.

and relevant axioms. The ontology approach has become popular in knowledge engineering and representation, yet it is novel in its application in various domains and its potential is still being explored. The ontology requires to be subjected to rigorous evaluation to verify functional specifications thereby ensuring consistency, reliability, accuracy, and extensibility.

To obtain accurate representation, undertake maintenance and efficient dissemination of semantic data (knowledge), the application of computational ontology strategies is proposed and therefore relevant for storage of ATHMed knowledge. In conformance with the DSR method, an additional round of verification on the ontology is required with the aid of domain experts. Hence, a further validation, involving verification and evaluation tests for reliability (Preece, 1994) to ascertain the performance capacity of the knowledge-based system is required. The objective is to measure the ontology's quality to guarantee adequate coverage of the knowledge appropriate to the ATHMed domain.

To derive the ontology, notable metadata representation tools, from authoring to languages for design and writing machine-readable and machine-understandable notation must be employed. This would require the use of Protégé, XML and extensible markup language (XML) Schema, resource definition framework (RDF) and Web Ontology Language (OWL-DL). This is to define appropriate metadata descriptions, structure and storage, and web resources for describing knowledge interrelation. In addition, these tools facilitate the definition of the ontology structure and semantics. Wollersheim and Rahayu (2005) suggest that as information (i.e., knowledge) becomes "explicitly connected", it evolves consequently becoming "semantically richer". Toward, the retrieval of data (knowledge) in the ontology-based KB, the value of adopting the ontology strategy is based on the possibility of obtaining reliable, contextual and semantically accurate results. This can be associated with the formalized definition of relationships (Wollersheim and Rahayu, 2005) coupled with the rigidity of constraints. This accounts for the approach proposed in the framework to enhance efficient retrieval of data especially during a search operation. The search and retrieval of the ontology-based data is facilitated through the information extractor component.

Information Extraction

From the framework, the search and retrieval mechanism are designed to be performed *via* a machine learning extractor that runs query requests against the ontology-based knowledge base. Thus, the information extractor is implemented *via* a machine learning-based (ML-based) extraction algorithm and an inference engine. The overall design is to enable the ML extractor work seamlessly on the ontology to produce semantically oriented results, based on the features stored in the ontology, taking critical considerations of class types, their relationships, instances, connotations and semantics. The ML extractor interacts with the inference engine to deduce new knowledge from the knowledge base (KB) to ensure accurate prediction and determination of appropriate treatment, association to ailment, preparation methods, and other relevant inferences. This, is anticipated, would yield relevant search results as the ontology is formulated on formalized, explicit relationships and axioms, and as such suited for knowledge-based systems especially in knowledge retrieval (Wollersheim and Rahayu, 2005). This, therefore, points toward the need to explore information retrieval strategies and natural language processing (text mining) capabilities which are applicable in knowledge-based systems.

Hersh (2015) views information retrieval (IR) as a field of study that deals with the "acquisition, organization and search of knowledge-based information". This infers that the information (knowledge) is often derived and organized from research (experimental or observational) and as such focuses on knowledge-based information. Hersh (2015) presents IR as a process that retrieves content suitable to the information needs of a person (user) processed by a search engine *via* a query that attempts to match content items through their metadata, executed based on two sub-processes: *indexing* and *retrieval*. The author further argues that these sub-processes constitute the two intellectual processes associated with information retrieval. Indexing here is referred to as a process that facilitates the assigning of metadata to content items (features). Retrieval, on the other hand, involves the submission of queries posed against the knowledge base that leads to retrieving (search, find and return) of content items (knowledge).

The information extraction's machine learning extractor sub-component is designed to interact semantically with the ontology based on the principle of finding and retrieving knowledge (content items) that fit the search description (query) passed by the user based on the metadata (ontology metadata) of the data (items) stored in the knowledge base. Metadata here focuses on Greenberg's (2003) description of metadata being "structured data about an object that supports functions associated with the designated object". By implication, for data to be efficiently retrieved an appropriate indexing strategy or mechanism must complement it during storage. Therefore, to obtain optimal results during retrieval of data from the knowledge base, consideration on an efficient indexing strategy suited to both ontology-based and machine learning facilitated knowledge base should be the focus. Additionally, the indexing strategy must be able to influence the retrieval of contextually fit and semantically oriented knowledge. The approach suggested in our framework is targeted at achieving this.

Indexing plays a critical role in the information retrieval process. Indexing can be done manually or automatically (Hersh, 2015), with the latter being preferred due to its obvious advantages of being more efficient, less expensive and applicable to larger and diverse data. Manual indexing involves the use of controlled terminology on a document (data) by human indexers based on some protocol. Automated, thus machine-assigned, indexing deals with the assignment of indexes on terms or words in some document (data). The latter approach is considered in our framework. According to Hersh (2015), indexing occurs by breaking out individual (atomic) indexing units (words, terms or concepts) and assigning them weight based on their frequency in the document (data) and in frequency in other documents. As such indexing is to be carried out at the word or sentence level which is compatible with classification levels and POST. It is expected that this approach will help build an appropriate structure for the data stored in the ontology knowledge base facilitating efficient retrieval.

Several indexing approaches have been suggested in literature. Most indexing approaches are perceived to match terms from some document to those of a query (Soe, 2014). Some of these approaches lean toward providing semantic capabilities suitable for searching ontologies. For instance, Soe (2014) proposed a context semantic index structure that performed superior to other approaches in the retrieval of data based on a context ontology. Therefore, the exploration of ontology-based indexing strategies, applicable to word or text indexing, which support semantic indexing that integrates with machine learning-based extraction mechanisms need to be considered. Additionally, as natural language processing capabilities are suggested in the framework, consideration of word or text indexing approaches is relevant. This is expected to affect how terms/word/features are captured and stored in the ontology-driven knowledge base. Further, it will assist in determining which approach the semantic reasoner deduces knowledge and makes accurate inferences.

The rate of success of the information extractor also is measured by what information/knowledge is retrieved. During retrieval, the relevant information searched and found is returned and/or presented to a user after a given query is submitted. In the retrieval process, an exact or partial match of search approaches can be used with each having its own constraints. However, since a careful annotation of data is to be presented for the classifier to learn, coupled with the need for accurate prediction of terms and concepts notable in healthcare delivery, the exact match search approach would be most suitable. This approach is considered to achieve a more precise prediction of terms relating to THMed knowledge while considering semantics and relevant association of concepts. As earlier indicated, the semantic reasoner presented in the framework acts as the inference engine. The inference engine structure is expected to work on the Java-based framework, Apache Jena. Machine learning techniques mainly to improve the efficiency of predictability, deduction accuracy and an extensible deeper learning approach shall be considered. This shall support the making of inferences whiles deducing new knowledge in a contextual form. This requires that the selected machine learning classifier be trained, initially on some rule-based approach before a well-structured corpus for ATHMed is defined and extended with the algorithm.

Subsequently, as depicted in the application layer, interaction with the knowledge base system is suggested to be performed *via* a graphical interface that is facilitated *via* the web or mobile platform. The aim is to achieve a high level of accessibility as these technologies are deemed ubiquitous and have shown the capacity to support use, anywhere and at any time with ease. Both platforms have the ability to support machine learning and ontology-based applications. Preferably, Android and J2EE technologies are proposed for the design and implementation of the mobile and web solutions, respectively. Users will be provided with simple interactive interfaces that communicative satisfactorily for them to pass simple to expressive statements as queries which will be received as natural language expressions. The use of natural language processing tools and techniques can facilitate efficiently such manipulations. This is to facilitate the extraction of relevant knowledge in the form required for adequate interpretation and understanding to the user. To this end, representation of the extracted knowledge must be textual and visual where required. Similar interface shall be presented to provide new knowledge to the knowledge base.

CONCEPTUALIZING THE IMPLEMENTATION OF ATHMED

Based on the core components discussed in the previous sections, a conceptual framework is presented. The framework seeks to provide an approach toward the implementation of a hybrid AI-driven (ML and Ontology) sustainable development of African traditional medicine. **Figure 5** presents a combination of problems existing in the ATHMed domain and the proposed sustainable solution. The conceptual framework has three main aspects that are serially aligned: The problem domain, the proposed solution, and the expected artifact. As earlier elucidated, the people in the problem domain are the stakeholders within the ATHMed environment who are practitioners, patrons/users, academics, researchers, and governmental agencies, who motivate the implementation of the KBS in ATHMed. The solution component proposes the KBS implementation strategy that considers the hybrid AI-driven approach in ATHMed. This proposed solution, as suggested in this study, considers a stream of data sources for ATHMed that are pre-processed and annotated to build the ontology model, constituting the knowledge base, suitable for efficient, contextual, semantic knowledge extraction by stakeholders.

The framework envisages an effective and sustainable approach to safeguarding, promoting, and disseminating ATHMed knowledge. The pragmatic approach to identifying, capturing, storing, and retrieval of knowledge on the preparation, application (use), and dissemination of traditional medicines will ensure its continuity, especially for the indigenous use of ATHMed. As earlier discussed, tacit knowledge of ATHMed held exclusively by some traditional healers can be captured and preserved using intelligent computing approaches such as knowledge-bases with AI approaches. Such an approach will enable the use of explicit ATHMed knowledge for formally training health workers in traditional medicine preparation and treatment. It is also geared toward facilitating the discovery of new medicinal properties of medicinal herbs and plants, and helping in advancing research into producing new medicines to serve the healthcare needs of ATHMed patrons. Potentially, this may lead to the conservation and preservation of flora and fauna that could be potential medicinal plants and thereby helping to sustain the local ecology of the communities where these herbs and plants are found. This, in effect, yields a more sustainable approach to healthcare delivery in the African context. Additionally, where the ATHMed knowledge bearer dies, the knowledge still exists in the KBS for future practitioners to learn, harness, and extend the practice of traditional herbal medicines with the needed scientific rigor that ensures safe and standardized preparation and use of ATHMed. This requires consistent collaboration between stakeholders within the domain and AI technology solution providers. This requires consultative engagement involving participatory problem identification, knowledge sharing, and feedback on solutions for ATHMed challenges. Thus, the concept of co-creation of a KBS based on a robust ML and Ontology strategy with stakeholders forms the basis of a sustainable approach to preserving and disseminating knowledge in the ATHMed domain. Consequently, this will help shape learning and training, drug preparation and standardization, and policy formulation within the ATHMed domain.

DISCUSSION AND LIMITATIONS

Discussion

The application of sustainable strategies to promote good healthcare is crucial in maintaining the wellbeing of a person. WHO (2019) reports that 88% of its member states, thus 170 countries worldwide, have acknowledged they use traditional herbal medicine (THMed). It further claims the "uniformly high use" of such healthcare practice further echoes the need to put in strategies, among others, to help ensure safety and monitoring, together with integrating THMed products, practices and practitioners into health systems (WHO, 2019). Accordingly, traditional herbal medicine has proven to be potent and is gaining global attention and use (Frass et al., 2012; WHO, 2019). This could be attributed to its often-natural form, ease of use, availability, and affordability. However, knowledge on these African traditional herbal medicines is gradually being lost if not lost already. The reason is that the knowledge on the preparation and administration of such medication often is tacit, orally communicated and poorly documented as indicated in literature (Yeboah, 2000; Adekannbi et al., 2014; Maluleka and Ngulube, 2018). The possibility of poorly trained ATHMed practitioners, who carry partial knowledge, administering poor medication which has consequentially harmful effects to their patrons is high (Yeboah, 2000). Yet many in the developing countries, especially in Africa, depend on ATHMed for their healthcare (James et al., 2018; WHO, 2019).

To help salvage the situation, deliberate calls and attempts have been made, by academia and research institutions worldwide, to help formalize and train THMed professionals. As custodians, these professionals will not only guide the processes and procedures to the preparation, preservation and administration of THMed, but also ensure the knowledge is not lost (Amoah et al., 2014; Poorna et al., 2014; Boadu and Asase, 2017; WHO, 2019). There are a plethora of reasons to actively pursue documentation, thus preservation and retrieval of ATHMed knowledge (Boadu and Asase, 2017). Poorna et al. (2014) report that countries who have employed meticulous

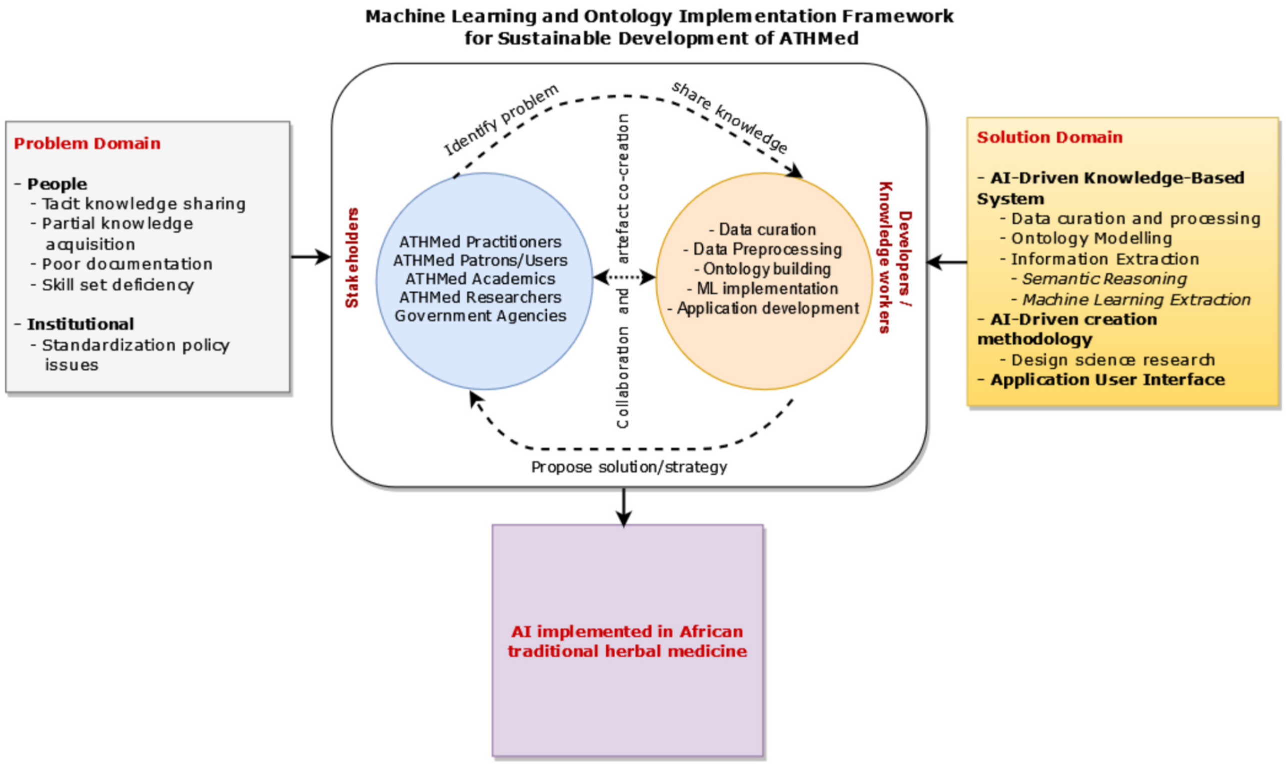

FIGURE 5 | Conceptual framework for machine learning and ontology driven sustainable development of ATHMed.

documentation (preservation and retrieval) strategies of their traditional (THMed) practices have yielded immense benefit to them. This reiterates the need for strategies that will help safeguard knowledge on African traditional herbal medicine and thus the proposed ATHMed framework. In essence, the impact of pursuing such THMed knowledge preservation and retrieval leads to key benefits to countries especially in Africa with obvious implications for healthcare benefits.

In an attempt to address the challenges of managing traditional herbal medicine, Atemezing and Pavón (2008) proposed an ontological approach for African Traditional Medicine (ATM) knowledge. Armel et al. (2011) proposed an approach that will enable Clinical Decision Support Systems access to knowledge of traditional doctors and patients to make patient-specific recommendations and provide explanations of their treatment based on deep ontology representation of ATM concepts. Kamsu-Foguem et al. (2013) proposed a framework to improve the formal requirements specification of African TM representation using ontological approaches toward improving the quality of ATM care while ensuring patient safety. Further, Omotosho et al. (2014) proposed a treatment system that used ontology approaches to design and represent Yoruba traditional medicine knowledge for diagnostic and therapeutic purposes. Similarly, Tekemetieu et al. (2016) developed a computer-aided system for ATM that uses ontology to describe knowledge concepts together with a multi-agent system that supports diagnosis and prescription of medicine. Thus, from extant literature, it is relevant to explore the hybrid strategy of ML and ontological approaches to help preserve and share ATHMed knowledge *via* a well-structured, computer-aided, and sustainable basis.

This current study confirms these challenges and finds that the traditional herbal medicine space in Ghana is not well-regulated and guided. The system allows fake and untested herbal medicine that are not monitored in the country. Our precipitants agreed that there is no robust and integrated system for the archival and retrieval of traditional herbal medicine in Ghana. They however blamed these challenges on the mandated regulatory bodies in Ghana. This brings to fore the relevance of the proposed framework in the study. The framework, to the best of our knowledge, is the first to address the challenge by bringing to the fore a *via*ble knowledge-based approach to salvaging potent medicinal knowledge hitherto tacit, facing the potential of being lost in time. The proposed knowledge-based system approach provides a rich-contextual knowledge base on the composition of African Traditional Herbal Medicine (ATHMed) for application and dissemination through a formalized teaching and learning curriculum, while employable for healthcare service delivery. This will form a base for extending research in the area of documenting, preserving, and sharing knowledge on ATHMed and its practices. Machine learning and ontology strategies were presented as a hybrid approach for the framework. This presents a novel approach to tackling issues involving the development of the knowledge-based system that seeks to formally and explicitly preserve and efficiently retrieve ATHMed knowledge in a semantically oriented pattern. The research culminates with an implementation of a framework for ATHMed.

Theoretically, as far as these authors are aware, the framework proposed *via* the hybrid approach is novel in the Ghanaian and largely African context particularly to the application of knowledge-based approaches to safeguarding traditional herbal knowledge. The literature reviewed suggests the integration of machine learning and ontology approaches in the preservation and retrieval of traditional medicine focusing on herbal medicine practices. This article, therefore, suggests useful approaches to consider within the knowledge management domain regarding knowledge-based systems and its application in safeguarding critical knowledge assets. Albeit the framework requires development, implementation and evaluation to ascertain its efficacy and veracity, it provides useful insights for further work. Additionally, the framework is targeted at archiving knowledge relevant for research and training of qualified herbal medicine professional who will ensure continuity and formalization of THMed practices in Higher Learning Institutions. The resulting output from academia will feed the pharmaceutical industry with the requisite knowledge on THMed. Causally, it is hoped that the development of the knowledge base will assist in the conservation of biodiversity, discovery of new bioactive agents and investigation of new herbal drugs for treatment (Boadu and Asase, 2017; Appiah et al., 2019). Although the ATHMed ontology to be developed as part of the knowledge-based system is targeted at suiting the Ghanaian herbal medicinal practices, it can be an excellent starting point to build generic KBs suitable in other similar regions as the modes of preparation of drugs and type of ingredients for herbal preparation and its intricacies may differ and cannot be carried in its entirety to fit the context of other group, regions or countries. The focus is to build a contextually fit ontology which will produce optimal results for the archival (preservation and retrieval) of ATHMed with the Ghanaian herbal medicine as the primary focus.

Practically, our framework and the subsequent development of the KBS is to influence how herbal practitioners undertake drug preparation and to assist in standardizing practices toward the formal training of such healthcare professionals. Additionally, the study intends to implement the KBS that will possess the potential of providing Medical Institutions of Higher Learning the needed repository of well-structured knowledge on ATHMed for research and the formal training of potential herbal doctors and pharmacists. In healthcare delivery, it would help address the concerns of lack of standards often attributed to some herbal products. Furthermore, as the knowledge is to be made assessable to all ATHMed stakeholders, policy and standardization issues (Chikezie and Ojiako, 2015) applicable to ATHMed practice can be made available to all *via* ubiquitous and platform-independent technologies as suggested in the framework.

When a healthcare organization has strong and organized financial management plans, it can provide efficient healthcare to all its patients. Contextualizing Artificial intelligence applications in the health sector ensures prudent financial management. DSR encourages co-creation with end-users. Research has shown that end users are more likely to use a system when they are made to be part of the artifact creation process. Developing an artifact without involving end users retrogresses the acceptance of the artifact and this disrupts prudent financial management. It is hoped that the application of the framework would influence further research into safer and standardized herbal medicines which may be more accessible to the needs of the citizenry and thus not require the use of scarce foreign exchange to purchase medicines that could be locally acquired. This will ensure affordable yet quality healthcare delivery to all, especially ATHMed patrons. There are also financial sustainability implications through potential job creation of new business in the herbal medicine value chain. Thus, livelihoods of indigenes of the countries who adopt and implement the framework, have a potential for improvement especially in the area of healthcare delivery while sustaining valuable biological resources. Poorna et al. (2014) indicated in their study that 6 countries who pursued safeguarding their traditional medicinal knowledge inherently promoted saving and securing patent to these national assets and by extension their cultural heritage. Our framework attempts to provide a sustainable approach to promoting long term use and rediscovery of knowledge helping to answer the call by WHO toward preserving THMed knowledge. In essence, the impact of pursuing such THMed knowledge preservation and retrieval leads to key benefits extending from health to cultural and historical relevance and economic benefits (Van Andel et al., 2015; Boadu and Asase, 2017; Appiah et al., 2019). While we seek to practically implement (develop) the framework in Ghana, we encourage other researchers in the domain to also implement or develop the proposed framework with proper acknowledgment.

Limitations and Future Direction

There are potential limitations that may hinder the implementation of the framework that could be related to human and technological factors. Considering the technological factor, the ability to adopt and apply appropriate technology for the preservation and retrieval of ATHMed knowledge may inhibit the possibilities of exploring the benefits of the AI-driven solution. Regarding the human factor, the willingness or otherwise of knowledge bearers (traditional medicine practitioners) to share their knowledge and also the acceptance and use of the stored knowledge for a more formalized training and standardized preparation of traditional medicine would determine the practical application, and in effect, the successful implementation of the framework. As this study is ongoing, we intend to automate this framework by leveraging the Design science research framework. Thus, stakeholders of traditional herbal medicine will be made to participate in the co-creation process.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary materials, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

EK, SD, and RA conceptualize the idea of the article, contributed to the drafting of the introduction, the background of the study, and reviewed and edited the article. EK and SD developed the framework and wrote the methodology. All authors contributed to the article and approved the submitted version.

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Autonomous Tool for Monitoring Multi-Morbidity Health Conditions in UAE and India

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Multi-morbidity is the presence of two or more long-term health conditions, including defined physical or mental health conditions, such as diabetes or schizophrenia. One of the regular and critical health cases is an elderly person with a multi-morbid health condition and special complications who lives alone. These patients are typically not familiar with advanced Information and Communications Technology (ICT), but they are comfortable using smart devices such as wearable watches and mobile phones. The use of ICT improves medical quality, promotes patient security and data security, lowers operational and administrative costs, and gives the people in charge to make informed decisions. Additionally, the use of ICT in healthcare practices greatly reduces human errors, enhances clinical outcomes, ramps up care coordination, boosts practice efficiencies, and helps in collecting data over time. The proposed research concept provides a natural technique to implement preventive health care innovative solutions since several health sensors are embedded in devices that autonomously monitor the patients' health conditions in real-time. This enhances the elder's limited ability to predict and respond to critical health situations. Autonomous monitoring can alert doctors and patients themselves of unexpected health conditions. Real-time monitoring, modeling, and predicting health conditions can trigger swift responses by doctors and health officials in case of emergencies. This study will use data science to stimulate discoveries and breakthroughs in the United Arab Emirates (UAE) and India, which will then be reproduced in other world areas to create major gains in health for people, communities, and populations.

Keywords: multi-morbidity, health, old age patients, autonomous tools, real-time

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INTRODUCTION

Researchers have collected massive amounts of data thanks to recent technological advancements throughout the world. Data availability and quality are important factors affecting our ability to improve individual and community health, from delivering treatment to performing scientific research, from rural clinics to the most modern genomics facilities. The capacity to completely extract relevant insights from this data will lead to faster discoveries and inventions that will positively influence health in the United Arab Emirates (UAE), India, and probably the rest of the world in due course. Rapid advances in data science, such as new methods to describe, collect, store, integrate, and analyze large scale, structured and unstructured heterogeneous data sets, as well as new data modeling methods such as artificial intelligence, machine learning, advanced deep learning, digital phenotypes, and three-dimensional imaging, are expected to have a high impact on the outcomes of behavioral and biomedical research leading to health improvement for populations and individuals, over the next decade. Traditional and publicly available datasets (e.g., surveillance, national health systems, and surveys) are becoming richer and deeper, while new other sources of datasets generated by new technologies and wearable sensors [e.g., social media streams, smartphones, global positioning system (GPS) data, wearables devices, electronic medical records datasets, genomics data, and bio-imaging] are emerging and being intensively explored for new opportunities and findings. Advances in diagnostics, technological development, and the possibility for public health are all based on progress in the generation of massive new data sets and sophisticated ways for mining hidden and interesting patterns of these datasets (Marston et al., 2019; Abuelkhail et al., 2021; Majnarić et al., 2021; Poongodi et al., 2021).

This study concept will use data science to stimulate discoveries and breakthroughs in the UAE and India, which will then be reproduced in other world areas to create major gains in health for people, communities, and populations. The multidisciplinary area of inquiry in which quantitative and analytical tools, procedures, and systems are developed and deployed to extract information and insights from increasingly massive and/or complicated quan1tities of data is described as data science in this study. Autonomous tool for monitoring multi-morbidity health conditions improves medical quality, promotes patient security and data security, lowers operational and administrative costs, and provides insights to the people in charge to make informed decisions.

Decades of infrastructure development and training in the UAE and India have created attractive research prospects to address the UAE and India's disproportionate part of the global illness burden. Data science has the potential to have a substantial influence on both qualitative and quantitative research and health in the UAE and India. New relevant, economical, acceptable, and scalable solutions may be produced by exploiting the current digital infrastructure. For example, in the UAE and India, widespread mobile phone service has resulted in significant advancements in banking, logistics, immigration, and other industries, including agriculture. It can also quickly develop healthcare delivery systems by bringing the clinic to the patient *via* point-of-care technology and self-management systems, with applications to rural and underserved communities worldwide. Also, as per UNESCO Human Development Index (HDI), UAE is considered very highly developed with a ranking being 31, while India is considered low with a ranking of 131. Contrasting best practices in these two extreme conditions facilitate broader learning and application from the proposed concepts. Following are the facets/applications of the proposed conceptual model:

Promote patient-centered healthcare at a lesser cost. Enhance the quality of care and information sharing among medical personnel.

- Educate health workers and patients through training.
- Encourage patients and healthcare providers to create new kinds of humane relationships.
- Cut down travel time and receive remote consultation, diagnosis, and treatment from specialists in far-flung facilities through telemedicine.
- Monitor public health threats.
- Promote patients' self-diagnosis or monitor illnesses.

INCREASING ICT USAGE TRENDS IN THE ELDERLY POPULATION GROUP

Figure 1[1] shows how seniors aged 60–69 years old had been closing the digital gap (in the sense of time spent online) compared to the total population.

One of the reasons that seniors have been catching up with younger generations is that each year, newer, more technologically savvy seniors replace older seniors who have reached the top limit of the age interval. Another explanation is that "new" seniors are more likely to find it simpler to adopt new internet habits once they reach retirement age. This is owing to their relatively high level of digital expertise, but it is also frequently due to family and friends who encourage them and want them to benefit from gadgets and applications for purposes such as communication, knowledge, or simply having fun.

However, as the COVID-19 crisis erupted, the generational digital divide ceased to close. Not because seniors used the internet less—in fact, they increased their use. The use of new technologies by the senior population greatly helps to a higher quality of life by increasing indices of everyday living such as transportation, communication, and social involvement. The older population is increasingly using modern technology than before. It is found that 77% of those over 65 years used the internet at home in 2020 (**Figure 1**). Similarly, it has been recorded that access to Internet/online services by old-aged women has doubled since 2011 (Marston et al., 2019).

Exploring the appropriate statistical variables and models for developing the machine learning component, which has been proposed in this study (**Figure 5**), extends findings from relevant prior research. The training phase of the model collects data variables primarily based on publicly available health conditions datasets. These variables include data about blood pressure, pulse oximetry, the concentration of glucose in the blood, activity tracking, sleep tracking with the corresponding prediction class; in addition to patient feedback and evaluation data (Dinsmore et al., 2021); finally, data related to health trajectories from Healthcare Administrative Databases (HADs) such as diagnoses and medication prescriptions are also included (Veronica et al., 2022). The production phase of the model collects data coming from the proposed tool and its associated sensory fabrics, as described in **Figures 2**, **4** to predict emergent

[1]Ericsson Consumer lab Analytical platform 2010-2020.

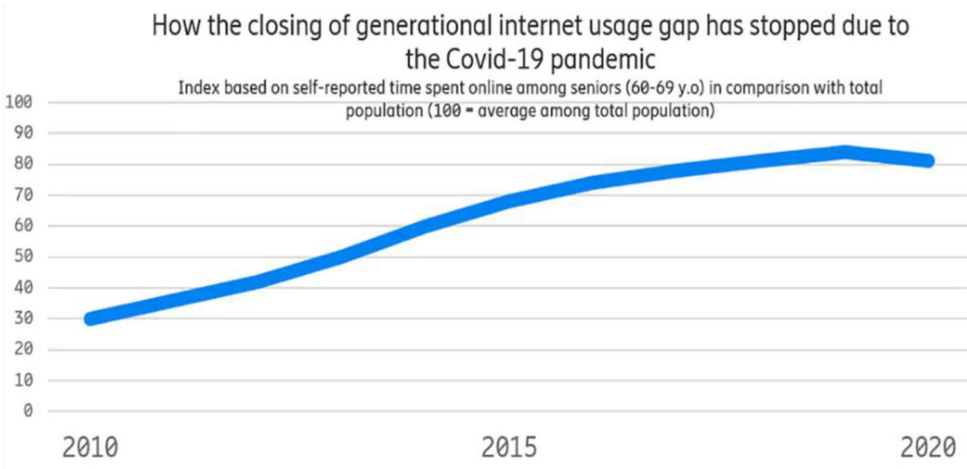

FIGURE 1 | How the internet usage gap has stopped since the outbreak of the pandemic.

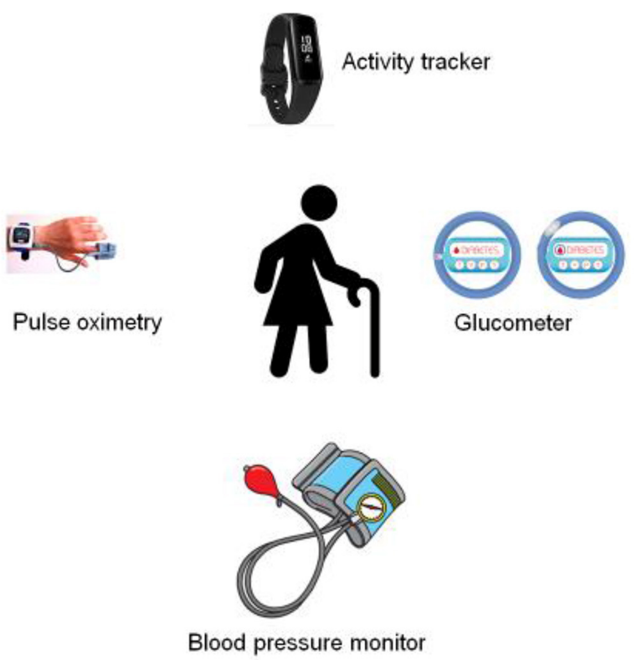

FIGURE 2 | Wearable sensor networks.

health situations requiring interventions such as early hospital admission, diagnosis, clinical procedures, and medications, will be compared with deep learning (DL) and convolutional neural network (CNN) (Nguyen et al., 2016; Pham et al., 2016) vs. traditional machine learning algorithms, e.g., Bayesian probabilistic model, k nearest neighbors, logistic regression, support vector machines, and decision tree (Deparis et al., 2018; Hansen et al., 2018; Khalid et al., 2018; Noh et al., 2019; Ben-Assuli and Padman, 2020; Franz et al., 2020; Veronica et al., 2022).

Notwithstanding, these traditional techniques suffers from multiple issues in real-time applications necessary in health application as they rely on feature selection and generation. Moreover, their performance decreases on high-dimensional datasets or large-scale datasets. To overcome the limitation of traditional methods, deep learning-based methods such as the convolutional neural network (CNN) model and long short-term memory (LSTM) models will be alternatively investigated.

The performance of the proposed machine learning algorithms will be assessed through relevant prediction score metrics, such as accuracy, F1-score, precision, and recall. The performance scalability of each algorithm will be evaluated based on the prediction latency time and system requirements in terms of processing and memory units. However, the proposed method will extend prior research in two specific innovative areas: first, assess the scalability performances of a holistic, big data framework to support the integration of several health applications to address the complex care needs of patients with multi-morbidity. Second, assess the performance of traditional and deep learning machine algorithms against several prediction accuracies and the production setup suitability for real-time healthcare applications targeting patients with multi-morbidity.

Research Scope

This research concept provides a natural technique[2] to implement a smart preventive health care solution. The proposed solution improves safer and more efficient patient care, such as elder persons with multi-morbidity diseases. The purpose

[2]The proposed conceptual technique featured as natural is based on the fact that the majority of the healthcare systems are migrating to ICT-enabled workstyle. Unfortunately monitoring, multi-morbidity health conditions have been overlooked by current research and development. It is naturally required to migrate this system to ICT-enabled facility, and this paper proposes the means to achieve it.

is to enhance the elder's limited ability to watch, predict and respond to critical health situations. Autonomous monitoring of the patient's health status and alert doctors and patients themselves helps lower unexpected health complications. The following four objectives help in achieving the research concept scope:

Objective-1: To redefine commodity technology requirements to monitor the health conditions of patients with multi-morbidity in real-time

- This research leverages smart devices such as wearable sensors and mobile phones for monitoring elderly persons with a multi-morbid health conditions that will work seamlessly anytime, anyplace for anyone. To achieve this objective, the specifications, functionalities, application, and technology requirements shall be identified and investigated to address the complex needs of elderly patients. This objective leverages the co-design approach (Spinuzzi, 2005) to involve all stakeholders to gather and the MoSCoW method (Clegg et al., 1994) to prioritize the system requirements.

Objective-2: To build a platform of autonomous health data collection and processing that will allow smooth interactions between patients, his/her mobile App, and the back-end big data platform

- Given the heterogeneity, ubiquity, and increasing autonomy of smart commodity devices, we foresee the need for a powerful mobile app and data management infrastructure specially designed to collect health information from thousands of diverse sources, providing their data in a variety of formats, granularities, and at different speeds, e.g., persons who suffer from two or more chronic diseases simultaneously. We also foresee the need to process these huge data streams in real-time. The system will therefore have to process directly as soon it is received instead of using the typical store-and-process paradigm (Sharma et al., 2021). The need to extract attributes from those data streams becomes extremely important for meaningful, higher-level information immediately accessible by Apps. The system shall provide users with simple and abstract APIs to access health data generated by devices without dealing separately with the underlying complexity of how data has been collected and data sources are connected to the system. In addition, the infrastructure shall provide a subscription/notification mechanism to notify events that are relevant to the subscribed systems/applications. Correlating and aggregating data sources would be a critical factor in detecting relevant pieces of key health information (Prisacaru et al., 2017).

Objective-3: To apply machine learning algorithms for predicting and responding to any critical health situations

- Once the health data are collected, the research proposes to customize the machine learning (ML) algorithms by applying a refined set of parameters to extract essential features that could be fed to ML models with the ability to predict and respond to any critical health situations with autonomous monitoring to alert doctors as well as patients of their unexpected health conditions.
- The results of the ML models are interpreted with the help of appropriate explainable artificial intelligence (AI) techniques.

Objective-4: To investigate the clinical validity of the holistic platform and its application performance scalability

- Results from Objective-2 and Objective-3 are expected to give more concise and precise accuracy in predicting and monitoring variables of the patient health conditions. We will observe effects between variables in our preliminary model that concur with the medical literature. Further developments would also include performance analysis of the method for a larger network, the inclusion of the temporal dimension, and different sampling rates per variable.

Significance

The proposed project would investigate and identify the best ways to integrate wearable sensors and mobile applications to observe the health condition of elderly people with multi-morbidity, including chronic heart failure, diabetes, and chronic obstructive pulmonary disease. The project provides intelligent and integrated platforms leveraging Wearable devices and sensors technologies to address the complex care needs of patients with multi-morbidity through monitoring the patients' health conditions in real-time. Moreover, applying data processing algorithms to the collected data for building predictive models to identify patients is likely to benefit from these models' recommendations and the timely interventions required. The study findings can significantly impact the way multi-morbidity health conditions are currently diagnosed in the UAE and India in terms of accuracy and robustness.

In addition, reducing human errors, enhancing clinical outcomes, increasing care coordination, boosting practice efficiencies, and collecting data over time are just some of the ways that the proposed conceptual framework can help improve and revolutionize healthcare.

LITERATURE REVIEW

Commodity devices such as wearable smartwatches and mobile phones have been widely investigated in several health monitoring applications as well as in context-aware situations complementing the elder's limited ability, i.e., rhinitis and asthma, heart rate, blood sugar levels, human body temperature, and fall detection enabled applications (Tarapiah et al., 2017; Bousquet et al., 2018; Mehmood et al., 2019). The integration of wearable and medical devices within home Internet of Things (IoT) based solutions were proposed by the European project entitled ProACT (Integrated Technology Systems for ProACTive Patient-Centered Care). ProACT described methods to observe the health condition of elderly people with multi-morbidity, including diabetes, chronic heart failure, and chronic obstructive pulmonary disease (Dinsmore et al., 2018; Malavasi et al., 2019; Adeniyi et al., 2021). However, very few researchers have been examining how to assess the scalability performances of

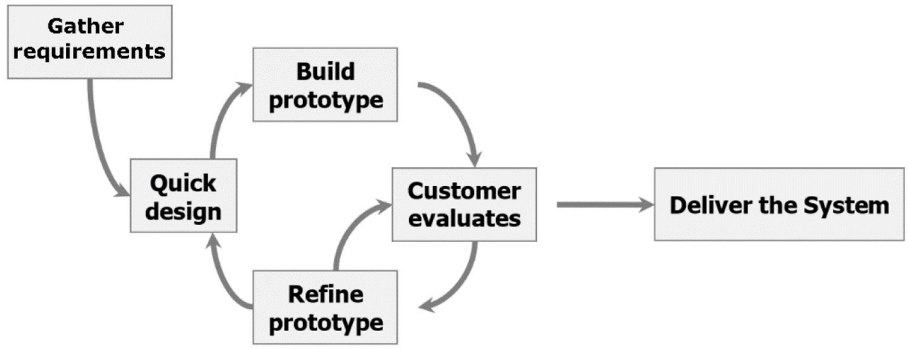

FIGURE 3 | Evolutionary prototyping methodology.

integrating several health applications into a single device to address the complex care needs of patients with multi-morbidity (Dinsmore et al., 2018; Waschkau et al., 2019). Further, few authors have proposed several data platforms leveraging big data technology that enable the discovery of emergent multi-morbid patterns and emanating longitudinal risk (Malecki et al., 2020; Kishor and Chakraborty, 2021).

Artificial intelligence algorithms such as classification, clustering analysis, and deep learning have been used to build machine learning predictive models to identify multi-morbid patients likely to benefit from these models' recommendations as well as for timely interventions required, for example, facilitate identification of patients having multi-morbidity conditions, disease diagnosis, and prediction system. The Bayesian network probabilistic method was proposed to model patients with multi-morbidity. The authors used features from patient vital signal measurements and activity tracking features. The training dataset was based on publicly available datasets from Irish elderly people, named TILDA (Deparis et al., 2018; Kishor and Chakraborty, 2021). Monitoring multi-morbidity conditions in real-time for thousands of patients simultaneously would generate many data streams. Consolidating these streams into a shared data platform poses the need for assessing the scalable performance of these platforms. However, the authors keep the doors open and pointed necessity to increase the prediction accuracy and to confirm the possibility of safely identifying the non-multi-morbidity patients from the multi-morbidity patients with confidence (Khalid et al., 2018; Noh et al., 2019; Franz et al., 2020).

CONCEPTUAL FRAMEWORK

Figure 3 displays the conceptual framework for addressing the research aims and objectives (mainly, objectives 1, 2, and 4). The main development architecture that will be used is prototyping methodology which involves designing and building the system in an agile and patient-centric way.

The standard systems development life cycle (SDLC) system development technique would be utilized to generate the project's final product. In addition, the SDLC will be supplemented by the evolutionary prototyping technique. This entails developing and building a functional scaled-down version of the system in a reliable and organized manner, then refining it through several stages until the final system is obtained. The system analyst would collaborate with the users to establish the fundamental needs. After that, the analyst creates a fast prototype and sends it to the user for feedback. The analyst refines the prototype based on the feedback and delivers the updated version back to the users. This process is repeated until the users are satisfied with the final output.

Improved user participation helps users submit more precise and explicit specifications and capture requirements in concrete form. The fact that the client is testing the prototype helps to keep the developer and client on the same page, improving understanding and communication. Increased engagement raises the possibility of delivering a final solution that will satisfy the stakeholders because the end-user is the most informed person in the problem domain. Furthermore, evolutionary prototyping suggests that the development team may misunderstand many requirements and that only well-understood requirements should be built. This reduces the danger of generating poorly understood components and encourages developers to focus on the parts they are familiar with.

The client can make suggestions for improvements and request adjustments after obtaining the partial prototype. In addition, prototyping saves time and money. Developers can recognize what the end-users want early on, resulting in speedier development and less expensive software.

Overall, the resulting evolutionary engineering, specification, and design methodology comply with the following broad template for each objective iteration: (1) Specification of functionalities for innovation and requirements for sustainable applications. (2) Requirements/innovation engineering and harmonization. (3) Architecture design specification and refinement. (4) Enabling technologies research to implement

TABLE 1 | KPIs for autonomous tool for monitoring multi-morbidity health conditions in UAE and India.

On-time completion %	Resource capacity %	Number of errors
Milestones on time%	Budget variance (planned vs. actual)	Customer complaints
Estimate to project completion	Budget iterations	Change requests
Adjustments to schedule	Planned value	Billable utilization
Planned vs. actual hours	Net promoter score	Return on investment (ROI)

the architecture and development in short/agile release cycles. (5) Prototype development of the platform, system integration, and testing. (6) Evaluation of the development platform in real application development.

Key Performance Indicators of the Proposed Conceptual Model

A key performance indicator (KPI) is a quantifiable performance measure over time for a specific strategic objective. KPIs provide targets for teams to shoot for, milestones to gauge progress, and insights that help people make better decisions. **Table 1** summarizes the key performance indicators of the proposed conceptual tool.

METHODOLOGY/APPROACH

The proposed methodology incorporates the principle of co-design, MoSCoW method, user experience, and human–computer interaction. A key aspect often underestimated is the human user interacting with the system. The proposed systems interact with humans to support their daily activities and increase their quality of life. The newest challenge seems to be incorporating human behavior as part of the system itself. The system will deal with large users locally, enabling interaction through dedicated context-aware HMI (human–machine interaction) dynamically reacting to the available system features.

Objective 1 Is Proposed to Be Achieved as Below

This objective aims to identify case scenarios and business models, including the stakeholders, end-user needs, and (non-) functional requirements for the technologies, products, and value chains, to deliver a new generation of the best ways to integrate wearable sensors and mobile applications to observer the health condition of elderly people with multi-morbidity of critical situations. In addition, the design work in this objective would carry out foresight and feasibility studies to identify architectural quality attributes, system requirements, and reusable core assets that would lead us toward a consolidated system architecture. The purpose is to distinguish a list of generic features for successful long-term deployment of the proposed application and a set of selected features that would be demonstrated in a variety of pilot studies. These pilot studies would be most helpful to analyze the impact of everyday use of our technology in society and identifying new business opportunities.

This objective leverages the co-design approach (Spinuzzi, 2005) to involve all stakeholders to gather and MoSCoW method (Clegg et al., 1994) to prioritize the system requirements.

Work Plan Steps

- Define the use cases regarding patient involvement and collect requirements amongst several health service providers by inquiring about external reference entities and literature reviews, workshops, etc.
- Analyze and specify requirements, document, and prioritize their rationale to avoid ambiguities and contradictions, and define the value chain for the described use case and service.
- Utilize the results achieved in the previous steps to define the use cases and their business requirements feeding the technical tasks of the proposal.
- Evaluate the use cases and services in a simulated environment with end-users and gather feedback.

Expected Outcomes

- Documentation of the requirements related to leveraging commodity devices such as a wearable smartwatch and a mobile phone app to support patients with multi-morbid health applications, specifically for implementation and demonstration.
- Based on prioritization, list a defined subset of use cases that bring enhanced and true value to the stakeholders through the new platform and system architecture.

Objective-2 Is Proposed to Be Achieved as Below

This objective aims to demonstrate the key concepts of the project proposal through the development of software platforms with concrete use cases from various components, such as personal sensor networks, Mobile App, and Big Data platforms, through real-life field trials. The objective is to show the proposal's principal innovations in terms of functionality and accuracy of its data capturing, transmission, processing techniques; applicability of the concept in different usage scenarios; easy deployment and seamless integration of the platforms; coexistence, in harmony, of different stakeholders (patient, doctors, health care services, application integrators) thus enabling a successful realization of the concept.

The proposed model, shown in **Figure 4**, would consider heterogeneous underlying sensors and network enabling technologies for convenient, near real-time network access to status information about the health conditions resources (e.g., heart rate, blood pressure) that can be monitored and controlled with minimal management efforts or doctors' interactions. The proposed system model in **Figure 4** depicts the main four layers of the proposed model, namely the devices and platforms, communication layer, Bigdata platform, and the applications layer.

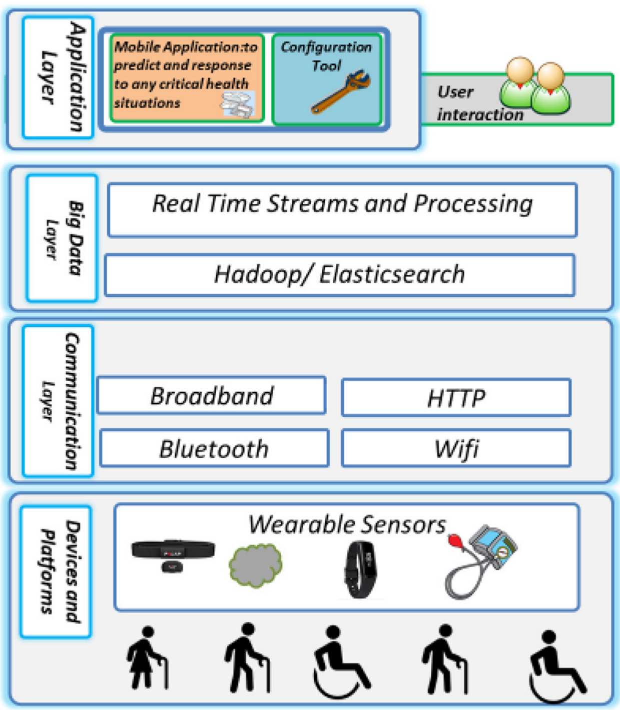

FIGURE 4 | The system model.

- The top layer: Here resides the User applications, data analytics, dashboards used to monitor and optimize the health-related operations.
- The big data platform: This component includes big data and the corresponding standard big data platform libraries that are suitable for addressing essential needs for handling various significant amounts of data, such as Hadoop/Elasticsearch, big data components for data storage, retrieval, organization, and analysis, as well as querying big data using Hadoop. Large-scale data analysis techniques, data storage platforms, data representations, and heterogeneous data models are all part of the project. The platform also contains the libraries and functions required by the hosting system to execute local, basic, and rapid processing and filtering on data generated or received locally.
- Communications layer: This layer offers near real-time connectivity and enables the communication between Devices and Platforms such as sensors to mobile, a sensor to the sensor, and mobile to a server within the ecosystem. It includes the networking protocols required to transfer the digital information from the sensors' layer to the application layers. Heterogeneous communication technologies exist from Wireless Fidelity (Wi-Fi), Bluetooth, Wireless sensor networks.
- Devices and platforms: The foundation layer of the wearable and infrastructure layer includes system apparatus components such as mobile and server platforms. Typically, a large volume of sensor devices is used to capture the status information about the patients' health condition to translate this information to the digital world notwithstanding the fact that a wide array of sensors devices is required to collect data about the patients. The main goal of the mobile platform is to aggregate the information collected by the sensors, mobile support heterogeneous data, and communications standards. The servers host the user's applications data repositories and provide unified access to Application Programming Interfaces (APIs) for other systems and users.

Work Plan

- A set of initial proofs of concept centered around selected use-case scenarios illustrating the wealth of applications and technologies brought together by the researchers.
- A sub-set of mid-term partially integrated demonstrations showing the initial results of the technical achievements obtained.
- A final demonstrator integrating the results of the project as a whole and show-casing the potential for large-scale deployment for real-world field trials with application scenarios.

Expected Outcomes

- Integrated platforms with mobile applications with basic decision-making algorithms with limited ability to predict and respond to any critical health situations; automatic monitoring can alert doctors and patients themselves of unexpected health conditions.
- Proof of concept based on the overall infrastructure utilizing all previously described components: personal sensor network, Mobile App, and Big Data Platform melting them to one comprehensive demonstration testbed.

Objective-3 Is Proposed to Be Achieved as Below

The aim is to develop algorithms that model and predict patients' health conditions. In the proposed platform, all smart devices ranging from low-end sensors mobile handhelds up to high-end service architectures—will interact with each other, and while doing so, they generate a stream of events in the network. Complex event processing and pattern recognition techniques will extract meaningful information for anticipating critical health conditions. By appropriately modeling event hierarchies and detecting causality between events, we will be able to transform simple events into high-level health conditions. The model must incorporate two aspects: (1) modeling component from a historical health dataset that includes publicly available health conditions with the corresponding decision making and predictions and (2) The real-time data streams generated by the wearable devices like blood pressure and heart rate etc., to forecast and predict the patient's current health conditions. The algorithm will exploit static information stored in the big data platform and in the mobile, as well as dynamic information acquired on the fly such as heart rate, activity tracking, etc. A prediction model can have three major components: (1) Target or outcome data: Data about the outcome that we want to predict, for instance, mortality risk; (2) Predictor data: Data used to make

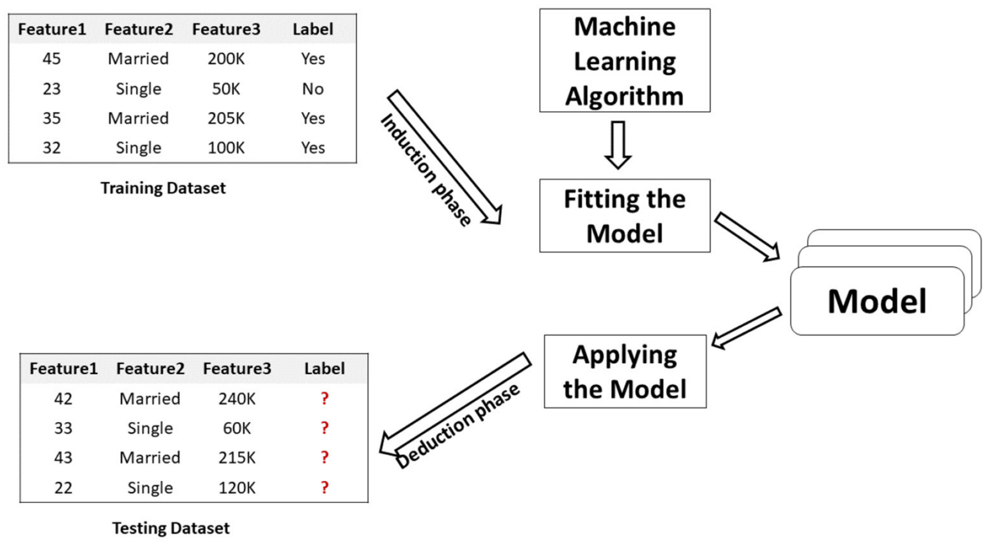

FIGURE 5 | ML application.

TABLE 2 | Stakeholder analysis matrix.

Stakeholder name	Contact person	Impact	Influence	What is important to the stakeholder?	How could the stakeholder contribute to the project?	How could the stakeholder block the project?	Strategy for engaging the stakeholder
End-Users: Patient with multi-morbidity	Phone, email address	High	High	Interact with the system on a day-to-day basis.	Agree for user interface design and functionalities to implement the new system	Reluctant to use the systems	Weekly round-table discussions
Health care authorities	Phone, email, website, address	High	High	Monitoring health conditions of the patients	Integration with the healthcare systems	Refuse to integrate new system with the health care system	Monthly round-table discussions
Doctors and health officials in case of emergencies.	Phone, email address	High	High	Monitoring health conditions of the patients	Identify system feature and accepted criteria	Reluctant to use the systems	Monthly round-table discussions
Application integrators	Phone, email address	High	High	Develop, test, integrate maintain functional system	Support the life cycle of the system		Daily round-table discussions

a prediction, for instance, patient symptoms, age, demographics, clinical history etc.; (3) ML model: A mathematical function that maps the relationship between the predictor data and the outcome data, for instance, decision trees, neural networks etc.

Figure 5 depicts the typical pipeline of an ML application, starting from the input training data set and ending with the corresponding output represented by the model. The model will follow the CRISP-DM lifecycle during the proposed conceptual framework's implementation, validation, and deployment.[3]

[3]The CRoss Industry Standard Process for Data Mining (CRISP-DM) is a process model with six phases (business understanding, data understanding, data preparation, modeling, evaluation and deployment), that naturally describes the data science life cycle.

While evaluating the ML models, the appropriate explainable AI methods will be leveraged. Explainable AI for the health care sector plays an important role in the proposed framework that helps understand and interpret predictions to the system end-user, patients and doctors.

Work Plan

- Investigate proper statistical and inferential representations for patients' health conditions variables that incorporate both knowledge information that is mainly edited by the researcher himself, and health variables information that is automatically generated through the proposed platform. For example, real-time health condition data and health trajectories.
- Identify appropriate learning and data mining techniques to detect anomalies in the data stream and their patient's activity—for example, machine learning methods such as Bayesian network and deep learning techniques.
- Integrate the discovered data models into the proposed platform.

Expected Outcomes

- Data-mining learning algorithms and information that could be used by decision-making algorithms with limited ability to predict and respond to any critical health situations.
- Proof of concept of the model integration in the platform.

Objective-4 Is Proposed to Be Achieved as Below

This objective aims to develop and execute an effective exploitation plan for clinical validity of the holistic platform and its application.

Work Plan

- Preparation of an initial exploitation plan and maintenance of the plan including the identification of relevant results and the corresponding target groups.
- Involvement of the external user in the planned demonstration phase.
- Compare clinical data collected and generated by the platform with clinical information from other sources to ensure the validity of the approach.

Expected Outcomes

- Exploitation and use plan.
- Joint proofs of concept with external user and health data sources provider.

Stakeholder Analysis Matrix

Table 2 Provides an initial list of the stakeholders and their expectations of the system.

PRIVACY AND SECURITY OF THE PROPOSED MODEL

As the proposed system contains highly sensitive scientific information, the system and data are prone to various levels of attacks. Following precautions that will be taken to fortify the privacy and security of the proposed conceptual framework

- **Information theft**—A suitable firewall will be installed on the servers to detect and protect from them malicious attacks.
- **DDoS attacks**—Several honey pots will be deployed to drive away attackers from the main data.
- **Ransomware**—All data stored on the server will be encrypted. Multiple copies of the sensitive and mission-critical information are backed up timely. A policy to use strong passwords and two-factor authentication with access tokens will be enabled.
- **Access control**—Different access control policies will be implemented.

INNOVATIONS IN THIS RESEARCH

Following are a few of the innovations from this research concept:

a. A software application and the back-end big data processing platform capable of autonomously monitoring the aged patients' health conditions in real-time serves to complement the elder's limited ability to anticipate and react to any critical health situations.
b. A truly consolidated software solution that enables autonomously monitoring the patients' health conditions in real-time serves the purpose of complementing the elder's limited ability to anticipate and react to any critical health situations.
c. Modern data science application has helped many patients decrease or sometimes even eradicate health condition uncertainty. It has helped doctors to harness information and bring an insight that might be useful for complex treatment progress such as cancer treatment.

Therefore, the proposed concept has the potential to create a whole new business ecosystem and exert social influence that may go way beyond the current health care system as we know it today. Both aspects are crucial for the acceptance and the wide deployment of such a system. Therefore, there is high potential for emerging new business opportunities and business models, which might benefit small and medium enterprises (SMEs) and the industry serving health care providers.

The project will be led by Dr. Shadi Atalla and supported by Dr. Saad Ali Amin and Dr. Manoj Kumar M V from Nitte Meenakshi Institute of Management (NMIT)- Bangalore, Dr. Nanda Kumar- from Ramaiah Medical College-Bangalore. Prof. Wathiq Mansoor will oversee the technical aspect of the project, while Prof. Ananth Rao will monitor and evaluate the project work plan and outcomes for timely completion of the project with financial assistance from local partners. NMIT, through Bangalore Ecosystem for Health Research (BEHR) network, would provide expert advice to the administrative core, data management core, and research projects on topics including data management; data analysis, including machine learning and artificial intelligence; and data visualization through its Data Management Analysis Core (DMAC) project.

SUSTAINABILITY

Sustainable practices improve the delivery of health care services in a variety of ways, from lowering the environmental impact of facilities to leading efforts to address public health hazards posed by climate change. Adopting sustainable practices in health care has the greatest impact by addressing the environmental and social determinants of health by building healthy living and working environments. The proposed conceptual model autonomous tool for Monitoring Multi-Morbidity Health Conditions in UAE and India will take almost every step to efficiently handle any sustainability-related issues right from the day one of implementation.

DATA SCIENCE TECHNOLOGY THAT IS BEING ADOPTED

Modern data science application has helped many patients decrease or sometimes even eradicate health condition uncertainty. It has helped doctors to harness information and bring an insight that might be useful for complex treatment progress such as cancer treatment. The project team would rely extensively on leveraging their experience of applying data mining and ML technologies to different scenarios ranging from data gathering, cleaning, processing, visualization, management, modeling, and finally producing reproducible data science products for building health care intelligent recommendations based on patient clustering and profiling. The project will use big data and the corresponding standard big data platform to address substantive needs for handling various significant amounts of data, such as Hadoop/Elasticsearch, big data components for data organization, storage, retrieval, and analysis, as well as querying big data with Hadoop. Large-scale data analysis, data storage systems, data representations, and semi-structured data models are all part of the project.

DATA SETS

There are many public repositories of data sets that contain health data sets. These data sets are typically public and open access and allow for testing algorithms very quickly. Such as Kaggle, UCI Machine Learning Repository, Big Cities Health Inventory Data, Healthcare Cost and Utilization Project (HCUP), data.gov, Kent Ridge Bio-medical Dataset, HealthData.gov, MHEALTH Dataset Data Set, and TILDA dataset. Notwithstanding, the validation of the phase of the project will rely intensively on simulated health data. These data will be gathered using commodity devices used by the researchers themselves. The system would be built and evaluated as part of a Proof of Concept Trial, which would take place at a trial site in Dubai. The system would be tested by the researchers to gain confidence in the prototype. Later the researchers can also include members of their network for pilot testing before large-scale validation in Dubai and India-Bangalore. Hence, public healthcare datasets would become essential in Dubai (available through our network), and India (publicly available through the Ministry of Health and Family Welfare database). These would be used to build Machine Learning Prediction Models.

DATA GOVERNANCE

The project team would encourage industry cooperation to harness current technology and cost-effective and sustainable solutions. The following SMART goals will be strictly implemented and made compliant with.

- Service cost model that is both sustainable and transparent.
- Follow worldwide authentication policies and services.
- Observe international data protection and anonymization standards.
- Metrics for performance and consumption will be measured and shared.
- Periodical data integrity check and reporting.
- Carry out risk-based validation.

APPLICATION PROGRAMMING INTERFACES AND INTEGRATION WITH LEGACY SYSTEMS

The proposed conceptual framework provides a user workspace to store, manage, compute, and share the user's data and analysis results with collaborators or the larger research community. Further, the architecture does provide a platform wherein users and researchers can also propose ideas or implementations that can be incorporated upon following the proper guidelines and policies of the proposed tool. It allows data to be combined across users and researchers in conjunction with other data openly accessible via the proposed tool. Researchers are also provided with open data APIs by the proposed tool, making the data accessible, understandable, and actionable, tailored to the unique needs of the authorized users or valid researchers.

Through multiple open-data APIs that may be made available to various collaborators utilizing portable Apps (web/mobile), the proposed tool enables portable tools to be deployed for one's personal usage, shared with collaborators, or free with the larger research community. The planned work is available under an open-source license and can be accessed *via* GIT, GITHUB, or other commercial platforms.

The proposed tool caters to a wide range of user personas, including novices and computationally sophisticated users, by offering a web interface as well as API access to data, tools, and computation, as well as facilitating integration with other systems. This is achieved by the proposed architecture's provision of resources that form the web portal via which registered users/researchers may have secure access to the data. The online portal will also feature usage guidelines and a few sample

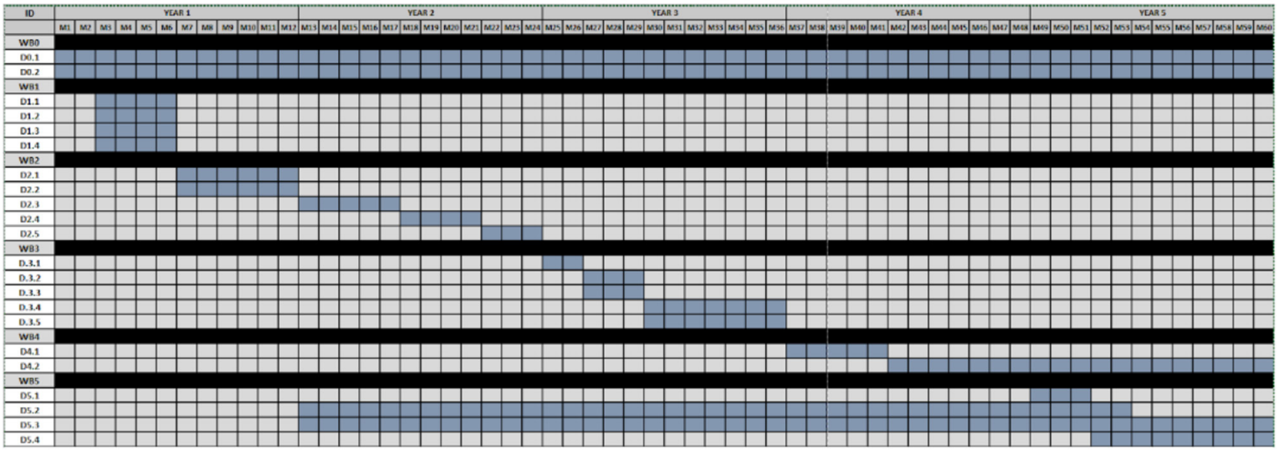

FIGURE 6 | Gantt chart of project milestones.

experiments for novice and experienced users to familiarize themselves with the site.

EXPECTED RESULTS

The project would provide an innovative integrated software solution for monitoring elderly persons experiencing multi-morbid health conditions. To achieve this result, several aspects of the system that spans from algorithms and mobile app to platforms would be closely investigated and continuously improved with innovations. The following list provides a short description of the most relevant results expected at the end of the project:

- The project would redefine application requirements and technical specifications to develop the described integrated software solution.
- The project would develop lightweight data communication mechanisms, protocols, and cryptography for privacy protection that are computationally inexpensive and require minimum bandwidth, implementable in simple devices, and flexible for distributed approaches.
- The project would provide a generic information model representing various system parameters such as network, software, security, and performance parameters data management operations.
- The project would provide a prototype of an autonomic, generic, and extensible execution platform that will allow smooth interactions between patients and its mobile application and the back-end big data platform.
- The project would improve the accuracy of the data mining predictive model to identify patients with critical health conditions.

COMMERCIALIZATION OF RESEARCH

As discussed in the foregoing sections, there exists a great potential for creating business opportunities and business models to benefit SMEs as well as the industry acting as health care providers. This ensures the scope for commercialization of the research concept and prototype in due course.

ETHICAL ISSUES

Although the project is focusing on the technical and implementation issues from big data platform and solutions perspectives, we cannot overlook the issues created by its possible global implementations such as ethics, policies, and legal issues that face computer professionals and data scientists while working with health and personal datasets, as well as the project, will examine the related cyber security issues.

LEGAL ISSUES

The project will maintain best practices and IEEE guidelines Intellectual Property, privacy issues, laws, and professional ethics governing these issues while working with the systems. The legal responsibilities need to be clearly defined in cases of system down or malfunctions by introducing new laws and regulations to handle and manage such cases.

CULTURAL AND SOCIAL IMPLICATION ISSUES

The system would introduce a significant social implication by changing the new way of interaction between the patients and their doctors, and its effect on the medical work lifestyle as with the new application, the doctor will always be aware of the patient's current health condition any time, and anywhere.

PROPOSED RESEARCH MILESTONES AND GANTT CHART

The proposed Project package breakdown structure and Gantt chart are shown in **Figure 6**, **Tables 3** and **4**.

TABLE 3 | Proposed project yearly plan.

Year of award	Months	Research activity milestones (team of 5 researchers formed already + 2 young researchers)
1st year	1–2	1. A team of 5 members will refine the research proposal; allocate responsibilities for each member, one to organize data, 3 to do literature review; 5th to organize the delivery of Objective 1
		2. Two young researchers with MS and fresh PhDs to train them in problem identification, literature review, hypothesis setting, Data Science tools being used, the process of Platform development.
	3–6	3. Define the application use cases and requirements
		4. A defined subset of use cases of the solution.
		5. Complete literature review
		6. Refine framework for the platform
	7–12	7. Develop the mobile application with basic decision-making algorithms.
		8. Integrate the Mobile App with described components: personal sensor network, medical devices, and wearables.
2nd year	1–4	1. Young researchers and the team (TEAM) to prepare draft paper for internal presentation in a research forum. Obtain feedback from forum peers.
		2. Revise the draft with the feedback
		3. Complete logistics for presenting the paper in 1st International Symposium.
		4. Refine framework for the Big Data platform
	5–8	5. Present the paper in the Bangalore Ecosystem for Health Research (BEHR) symposium
		6. Obtain feedback from symposium participants
		7. Incorporate feedback to publish the symposium proceedings
		8. Disseminate the research results technically to the local UAE and Indian community through social media channels.
		9. Integrate the Mobile App with the BigData Platform
	9–12	10. Submit the proceedings to a peer-reviewed journal
		11. Develop proof of concept based on the overall Solution infrastructure
		12. Refine the AT tools for commercial.
3rd year	1–2	1. A team of 5 members will refine objective 3 of the research proposal; allocate responsibilities for each member, one to organize data, 2 to do literature review; 4th to organize the delivery of Objective 3 and 4
		2. 2 young researchers to train them in problem identification, literature review, hypothesis setting, Machine learning tools being used, process of Autonomous Tool (AT) integration the ML models with the solution platform.
	3–6	3. Complete collection of existing publicly available and/or UAE and Indian data.
		4. Refine the literature review with a focus on machine learning.
		5. Refine framework for the AT for the integration ML model.
		6. Set Hypotheses and goals.
	7–12	7. Integrate the AT
		8. Run experiments with in-sample data
		9. Validate the AT using test data or validation data
		10. Start preliminary analysis on initial results
		11. Apply AT on the population: researchers themselves and their relatives
		12. Get feedback from the population on the merit and demit of using the AT for improving their health.
		13. Use the feedback as additional data and feed to the AT tools
		14. See the improvements in the results
		15. Iterate the cycle 11–14 three times to cover at least the sample number of patients in the local population to get a decent response.
		13. Conduct community forums to disseminate the iterated results
4th year	1–4	1. Young researchers and the team (TEAM) to prepare draft of the second paper for internal presentation in a research forum. Obtain feedback from forum peers.
		2. Revise the draft with the feedback
		3. Complete logistics for presenting the paper in 2nd DS- I UAE and India Symposium
	5–8	4. Present the paper in the Bangalore Ecosystem for Health Research (BEHR) symposium
		5. Obtain feedback from symposium participants
	9–12	6. Incorporate feedback to publish the symposium proceedings
		7. Submit the proceedings to a peer-reviewed journal

(Continued)

TABLE 3 | Continued

Year of award	Months	Research activity milestones (team of 5 researchers formed already + 2 young researchers)
5th year	1–4	1. The Team members will refine objective 4 of the research proposal; allocate responsibilities for each member, one to commercialize the tool by patenting its data, 2 to Disseminate in non-technical; 2 to organize the delivery of the exploitation plan
	5–8	2. Disseminate in a non-technical manner the research results to the local UAE and Indian community through social media channels
		3. Preparation of an initial exploitation plan and maintenance of the plan including the identification of relevant results and the corresponding target groups.
		Involvement of the external user in the planned demonstration phase
	9–12	4. Compare Clinical data collected and generated by the platform with clinical from other sources to ensure the validity of the approach
		5. Joined proofs of concept with external user and health data sources provider.
		6. Closure of the research project with a summary of lessons learned and experiences gained by the TEAM for future

WB, Work Breakdown; Description: (M—Month; PM—Project Month).

TABLE 4 | Project work breakdown structure.

WB	Work breakdown title	PM	Start	End
WB0	**Project management**	5	M1	M60
D0.1	Administrative project management	5	M1	M60
D0.2	Impact management	5	M1	M60
WB1	Cases requirements gathering and literature review			
D1.1	Use cases and user requirements	7	M3	M6
D1.2	Use cases of the proposed solution	7	M3	M6
D1.3	Objective 1 and 2 literature review	4	M3	M6
D1.4	Refine framework for the platform	4	M3	M6
WB2	Platform development and implementation			
D2.1	Mobile application with basic decision-making algorithms.	5	M7	M12
D2.2	Integrate the Mobile App with medical devices, and wearables	5	M7	M12
D2.3	Refine framework for The BigData Platform	5	M13	M17
D2.4	Integrate the Mobile App with the BigData Platform	5	M18	M21
D2.5	Develop proof of concept based on the overall solution infrastructure	5	M22	M24
WB3	Machine Learning and Autonomous Tool (AT) integration			
D3.1	Literature review with focus on machine learning	7	M23	M24
D3.2	Data identification and collection	7	M25	M28
D3.3	Refine framework for the AT for the integration ML model	7	M25	M28
D3.4	Set hypotheses and goals	7	M29	M36
D3.5	Building data models	7	M29	M36
WB4	Integration and testing			
D4.1	Integrate the Machine learning Model with the Platform	5	M37	M40
D4.2	Run testing scenarios	7	M41	M60
WB5	Evolution, dissemination evolution exploitation			
D5.1	Preparation of an initial exploitation plan and maintenance	7	M49	M51
D5.2	Platform evaluation and validation		M13	M56
D5.3	Publication and commercialization	7	M13	M60
D5.4	Disseminate in non-technical manner	7	M52	M60

CONCLUSION

The proposed research concept aims at integrating several real-time monitoring technologies and data science methods to promote a safe and independent living of the elderly multi-morbidity patients through health data sharing and communication between patients and healthcare professionals. The solution relies on the interaction of the elderly persons with multi-morbidity diseases with commodity devices to enhance the elder's limited ability to watch, predict and respond to any critical health situation. In conclusion, autonomous observance of the patient's conditions along with vigilant doctors and patients themselves will help to minimize the unexpected health complications.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Predicting Universal Healthcare Through Health Financial Management for Sustainable Development in BRICS, GCC, and AUKUS Economic Blocks

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The majority of the world's population is still facing difficulties in getting access to primary healthcare facilities. Universal health coverage (UHC) proposes access to high-quality, affordable primary healthcare for all. The 17 UN sustainable development goals (SDGs) are expected to be executed and achieved by all the 193 countries through national sustainable development strategies and multi-stakeholder partnerships. This article addresses SDG 3.8—access to good quality and affordable healthcare and two subindicators related to societal impact (SDG 3.8.1 and 3.8.2) through two objectives. The first objective is to determine whether health expenditure indicators (HEIs) drive UHC, and the second objective is to analyze the importance of key determinants and their interactions with UHC in three economic blocks: emerging Gulf Cooperation Council (GCC); developing Brazil, Russia, India, China, and South Africa (BRICS) *vis-à-vis* the developed Australia, UK, and USA (AUKUS). We use the WHO Global Health Indicator database and UHC periodical surveys to evaluate the hypotheses. We apply state-of-the-art machine learning (ML) models and ordinary least square (traditional—OLS regression) methods to see the superiority of artificial intelligence (AI) over traditional ones. The ML Random Forest Tree method is found to be superior to the OLS model in terms of lower root mean square error (RMSE). The ML results indicate that domestic private health expenditure (PVT-D), out-of-pocket expenditure (OOPS) per Capita in US dollars, and voluntary health insurance (VHI) as a percentage of current health expenditure (CHE) are the key factors influencing UHC across the three economic blocks. Our findings have implications for drafting health and finance sector public policies, such as providing affordable social health insurance to the weaker sections of the population, making insurance premiums less expensive and affordable for the masses, and designing healthcare financing policies that are beneficial to the masses. UHC is an important determinant of health for all and requires an in-depth analysis of related factors.

Policymakers are often faced with the challenge of prioritizing the economic needs of sectors such as education and food safety, making it difficult for healthcare to receive its due share. In this context, this article attempts to identify the key components that may influence the attainment of UHC and enable policy changes to address them more effectively and efficiently.

Keywords: UHC, healthcare financial management, sustainable development, artificial intelligence, universal health coverage (UHC), sustainable development goal (SDG)

BACKGROUND

The main goal of universal healthcare is to make healthcare affordable and accessible to every person on the planet without financial hardship. Universal health coverage (UHC) is a key aspect of achieving the two primary goals of the World Bank Group (WBG). The primary goal is to eradicate extreme poverty and facilitate shared prosperity. UHC is a key driver of all WBG projects related to health and nutrition. UHC focuses primarily on empowering and investing in human capital, which is the primary strength of any country. Without quality human capital, children will be unable to go to school and adults will not be able to go to work. Healthcare constitutes the largest sector of the global economy. The healthcare sector currently employs more than 50 million professionals (the majority of them are dominated by women).

Sustainable development goal (SDG) 3.8 is to facilitate UHC, which includes access to affordable healthcare services, financial risk protection, and access to safe, effective, quality medicines and vaccines for all. SDG 3.8 complements the objectives of SDG 1, whose primary goal is the eradication of poverty, which is impossible without stringent enforcement of UHC (United Nations Sustainable Development Indicators., 2019).

Immediately after the UN high-level meeting on UHC (in September 2019), it was noted that UHC is gaining global traction. Member states overwhelmingly endorsed a political declaration reaffirming their high-level political commitment to UHC and specifying the number of critical activities. In total, 12 cosignatories, including the WBG, have established the global action plan (GAP) for healthy lives and well-being for all to assist nations in collectively achieving the SDG3 objectives. Subsequently, in January 2020, the second UHC conclave was held to further boost the political involvement of UHC in the international platform.

Universal health coverage stresses access to primary health services. The most beneficial sector of UHC is human capital. Human capital, such as women, children, adolescents, and people with mental disorders, will benefit significantly. On the other hand, it is alarming to note that, if current healthcare trends continue, 5 billion people will be unable to access even primary healthcare services by 2030. Furthermore, it is also predicted that maternal and infant mortality rates will ramp up in several parts of the world. To counter this healthcare threat, the Global Financing Facility (GFF) was set up by the WBG in 2015. The main focus of the GFF is to help countries improve healthcare facilities for children, mothers, and adolescents.

The employment of the younger workforce will significantly fuel economic growth and, thereby helps in the eradication of poverty. It is the elected government's responsibility to invest in enhancing human capital. This can only be done by improving the quality of healthcare and prosperity. Enhancing reproductive, maternal, neonatal, child, and adolescent health (RMNCAH) and managing mental health issues are critical steps toward UHC. Significant problems exist, including the following:

- *Maternal Mortality:* The share of maternal mortality in developing nations is increasing year by year. It has been observed that the risk of maternal mortality is on average 1 in 56 as opposed to 1 in 7,800 in developed countries. In South Asia, 20% of maternal deaths are normally reported. Most of these deaths could be avoided if these women were given the necessary healthcare in time.
- *Child Mortality:* According to the study carried out by the World Health Organization (WHO), the World Bank, and UNICEF, there is a considerable decline in the percentage of child mortality between 1990 and 2018. It is sad to note that current healthcare data report that an average of 15,000 children under the age of 5 die every day. In addition, the WBG, WHO, and UNICEF partnered on another 2020 publication that focused on stillbirths, a problem that is often ignored. Every year, 2 million infants are stillborn worldwide, and success in lowering these numbers has lagged behind the drop in under-five mortality. In 2000, the ratio of stillbirths to deaths among children under the age of 5 was 0.30; by 2019, it had risen to 0.38 globally.
- *High Fertility*: Women are having fewer children now than they did three decades ago. Countries with high fertility frequently have high maternal, newborn, and infant mortality rates.
- *Adolescent Fertility:* In nations with high fertility rates, more adolescents give birth. Underage mothers are more likely to suffer from pregnancy problems such as obstructed labor and eclampsia, increasing their chance of mortality. Adolescent-born children are also more likely to have low birth weight, illness, stunting, and other nutritional problems.

Mental, Neurological, and Substance Use Disorders (MNS): These prevalent, severely debilitating illnesses are linked to considerable early mortality and impose a human, societal, and economic toll. Every 40 s, someone in the world commits suicide.

To ultimately accomplish the purpose of UHC and increase human capital results globally, mental health initiatives must be linked to community service delivery and protected by financial protection structures. According to estimates, almost 1 billion individuals have a mental condition. More than 75% of patients with the illness do not obtain treatment in low-income nations. By the age of 14, over half of all mental health illnesses have emerged, and around 20% of children and adolescents globally have some form of mental disease. More than one in every five persons (22.1%) have mental illness in nations afflicted by war and violence. Women and children who have witnessed violence, soldiers returning from the battle, migrants and refugees displaced by conflict, the destitute, and other vulnerable groups are disproportionately impacted. The COVID-19 epidemic has resulted in a global spike in mental health issues due to several variables such as anxiety, lockdowns, job losses, disturbing, or perhaps suspending, key mental health services in 93% of countries worldwide.

Mental, neurological, and substance use disorders have an early age of onset—often in infancy or early adolescence—and are disproportionately frequent in the working-age population, contributing to worldwide economic production losses estimated at \$2.5–8.5 trillion, which are expected to almost three times by 2030.

The Japanese Presidency held the first-ever combined session of G20 Finance and Health Ministers in June 2019. The debate was intended to rally G20 countries around the unifying goal of funding UHC in underdeveloped countries. A World Bank analysis revealed that individuals in underdeveloped nations pay half a trillion dollars per year—more than \$80 per person—out of their own pockets to receive healthcare. Such costs disproportionately affect the poor and jeopardize decades of healthcare improvement.

According to the 2019 World Bank/WHO study, nations must raise expenditure on primary healthcare by at least 1% of their gross domestic product (GDP) if the world addresses glaring coverage gaps and reaches the health objectives agreed upon under the SDGs. A lack of universal access to high-quality affordable healthcare jeopardizes countries' long-term economic prospects and renders them more vulnerable to pandemic threats.

Without immediate action, developing countries confronted with aging populations and increasing burdens of noncommunicable diseases will face increasing challenges in closing the gap between the demand for health spending and available public resources, extending patients' and their families' reliance on out-of-pocket spending[1].

Uniqueness

A more significant amount of analytical work is required at the global and regional block level to better understand who suffers from financial hardship, what are the causes of financial hardship, what are the consequences of financial hardship in the short- and long-term, and how households attempt to mitigate financial hardship in the short-term by borrowing or depleting their assets, Furthermore, how health system features can reduce or increase financial hardship. There is very sparse empirical work done on these problems globally and in developing countries in economic blocks like Gulf Cooperation Council (GCC) and Brazil, Russia, India, China, and South Africa (BRICS) compared to developed economies in blocks like Australia, the UK, and the USA (AUKUS). Hence, this research adds to the academic and practice literature to help policymakers take appropriate action to achieve the targets set under 3.8.1 and 3.8.2 in these economies by 2030.

Innovation

This article applies an artificial intelligence (AI) tool through Random Forest modeling to analyze the data and demonstrates its superiority over conventional ordinary least square (OLS) regression methods traditionally found in earlier studies.

Significance

The significance of this research includes the following contributions:

- Improving border epidemic and pandemic public health surveillance (PHS) capacities in India–UAE. This objective is reached by analyzing and contrasting the health security status of the UAE and India methodically.
- Increasing PHS workforce in India and the UAE. We are developing a capacity-building ontology framework and training curriculum (with stakeholder feedback and field testing) to manage SDG and Global Health Security Agenda (GHSA) gaps in human, animal, and environmental departments.
- Expanding India's and the UAEs' present field epidemiology capacity to better identify and mitigate diseases and pandemics in the region.
- Increasing emergency preparedness in India–UAE to better control and prevent disease outbreaks in the region.
- Improving electronic disease surveillance across India and the UAE by supporting the GHSA and deploying surveillance activities.

RESEARCH PROBLEM

In 2015, all the 193 UN member states accepted the 2030 Agenda for sustainable development (SD) and the 17 SDGs. This global agenda's implementation and achievement will depend on all nations and necessitate national sustainable development strategies and multi-stakeholder partnerships. Six fundamental transformations must occur to fulfill the SDGs. Each of the six transitions necessitates a significant increase in public investments. The financial requirements of these SDG initiatives exceed the budgetary space available to governments in low-income developing nations (LIDCs). To attain the SDGs, LIDCs will need to enlarge their budgetary space significantly, which would require a mix of local and global fiscal measures. This article focuses on the second transformation—access to high-quality affordable healthcare—and two sub-indicators, 3.8.1 and 3.8.2, to assure

[1] https://www.worldbank.org/en/topic/universalhealthcoverage#1

societal effect. The contribution of this manuscript would be improved health and safety outcomes through universal healthcare and would pave the path for public-sector policy change or influence.

Indicators of financial protection show inconsistent results between 2000 and 2019 in preventing people from encountering financial hardship (while paying for healthcare out-of-pocket). The number of people and the percentage of the population impoverished by out-of-pocket health spending at the thresholds of $1.90 and $3.20 per person per day. At the same time, an increasing share of the population is experiencing out-of-pocket healthcare costs. Previous worldwide studies have shown that as nations get wealthier, citizens endure greater financial difficulty due to increased reliance on out-of-pocket spending.

The policy challenge is to guarantee that increased healthcare resources are channeled through mandatory pooled prepayment arrangements rather than out-of-pocket payments, which results in access inequalities across various income strata.

Specific Research Objectives

In the light of the foretasted problem, the specific objectives of this article are as follows:

1. To explore whether health expenditure indicators (HEI) drive the UHC index.
2. To assess the level of importance and degree of impact of HEI on UHC in emerging GCC and BRICS compared to the developed AUKUS economic block.

Hypotheses

The research objectives are evaluated through the following sets of general and specific hypotheses.

General

- The higher the current health expenditure (CHE) as % of GDP for various healthcare, the higher will be the UHC.
- The higher the out-of-pocket expenses by the household for healthcare, the lower will be the UHC.
- The higher the compulsory health financing arrangements as % of CHE, the higher will be the UHC.
- The higher the government health financing arrangement as % of CHE, the higher will be the UHC.
- The higher the voluntary health financing arrangement as % of CHE, the higher will be the UHC.
- The machine learning (ML) technique is more appropriate for predicting UHC than the traditional OLS technique.

Specific Hypotheses

Universal health coverage is a complex function of health and non-health determinants. The influence of a given variable varies between different geographies and economies. The interactions of the variables within the model will provide a clear indication for policymakers to emphasize the same while drawing up programs for addressing the same.

Therefore, the specific hypothesis states that the importance of each input and control factor varies across the three blocks and that the impact factors (synaptic weights in the ML model) also differ across the blocks.

Rationale for Focusing on the BRICS, GCC, and AUKUS

Brazil, Russia, India, China, and South Africa are an economic block of the world's most significant growing economies, accounting for 41% of the worldwide population, 24% of worldwide GDP, and more than 16% of universal trade (World Health Organization, 2021). The varying proportions of infectious and chronic lifestyle diseases exhibit a distinct pattern regarding morbidity and mortality across the economic blocks. The BRICS have fueled economic advancement throughout the years. BRICS nations differ substantially in terms of illness loads, healthcare systems, interests in global pharmaceutical trade, international participation, and many other factors. The rise of the BRICS as a unique organization with rising degrees of transnational cooperation in health and other activities puts pressure on existing and new global governance systems and procedures. Many of those who advocate for UHC, whether as scholars, lawmakers, or consultants, look to national governments and regional or other blocks for leadership and inspiration. Some countries that have historically supplied such leadership have mostly retreated, leaving a need that the BRICS may potentially fill. More study is needed to determine whether this gap exists, whether it is significant, and whether the BRICS can fill it (McKee et al., 2014; Watt et al., 2014; Wagstaff et al., 2018b).

To move closer to UHC, the BRICS have implemented health system changes. Despite the fact that national governments have played a significant part in these changes, private financing accounts for a significant portion of BRICS health spending. China and India rely heavily on direct expenditures, whereas Brazil and South Africa rely heavily on private insurance. Brazilian health reforms resulted from a political campaign that established health as a constitutional right. On the other hand, those in China, India, the Russian Federation, and South Africa were an attempt to enhance public sector performance and eliminate disparities in access. The transition to universal healthcare has been sluggish. Reforms in China and India have not effectively addressed the issue of out-of-pocket expenses. Negotiations between national and subnational institutions have sometimes proven difficult, but Brazil has established strong cooperation between federal and state authorities *via* a constitutional definition of authority. Poor coordination has resulted in fragmented pooling and inefficient resource usage in the Russian Federation. It is critical to utilize public and private sector resources in mixed health systems (Rao et al., 2014). The BRICS are dedicated to disseminating lessons learned from their recent experiences. These nations are progressively fostering the development of different global health programs, including UHC, by providing diplomatic support and serving as technical resources. Representatives of the BRICS nations, for example, "emphasized the significance of UHC as a key tool for the realization of the right to health" during the 65th World Health Assembly in 2012 (O'Neill, 2001).

Gulf Cooperation Council

The GCC has a UHC service coverage index of 72.5% (World Bank, 2021). The GCC and BRICS economies are active, vigorous, and favorable to economic divergence. As a result, they draw capital influxes from foreign investors as the GCC and BRICS countries continue to make inroads into global economics and experience faster economic development than industrialized nations mired in a slow-growth atmosphere (Bhuyan et al., 2016). According to World Federation of Exchanges statistics at the end of 2015, the total market capitalization of the GCC and BRICS nations is US$12,809 trillion, which is US$1,200 trillion more than the entire joint market capitalization of Europe, the Middle East, and Africa. Furthermore, the GCC and BRICS economies are the origins of significant sources of demand and supply.

The UAE has about 11.5% of its population as citizens, with the rest, 88.5%, made up of expatriate employees as of 2018. South Asians make up 59.4% of non-UAE nationality. Similar to developing markets, the GCC and BRICS markets are subject to macroeconomic and global market circumstances (Mensi et al., 2014).

Internal variables play an essential role in driving economic and financial conditions in the GCC and BRICS nations. There is much evidence that foreign influences drive many of the GCC and BRICS countries' economic and financial conditions. Undoubtedly, the healthy economic circumstances in the AUKUS and the rest of the developed countries benefit the economies of the GCC and BRICS, which share critical strategic commodities such as gold and crude oil. China and India are two of the world's most significant users of crude oil. On the other hand, Russia is one of the world's top crude oil and natural gas producers, with economic linkages to industrialized economies. In contrast, deteriorating economic circumstances in developed economies would decrease GCC and BRICS exports to developed markets and decrease funds and capital influxes from advanced to GCC and BRICS economies.

The GCC block is oil-rich and has enough potential to drive and lead UHC. The model adopted by the rich GCC block can be tuned and adopted by the rest of the economic blocks, especially in the BRICS countries. The BRICS is a potential unit of leading information technology collaboration. India's 2022 information technology-related exports are expected to touch new heights. A positive growth rate of 4.7% is expected to be achieved in the Indian export industry. The following are the unique predictions from the perspective of India alone:

- It is estimated to cross the US$ 400 billion mark concerning outbound shipments.
- The world trade organization (WTO) predicts that India can increase its exports by 4.7% in 2022.
- It has been estimated that software exports will cross the line of US$ 148 billion. This is more than the oil sales of the GCC countries.
- In the coming months of 2022, India is expected to experience exponential growth in software companies.

Because the BRICS have the world's most significant engineering population, the software export business in the BRICS has the potential to soar in 2022 and thereafter. Although software exports are a component of export-led growth stories, they appear to be gaining traction in recent years.

Australia, the UK, and the USA block is a trilateral technology accelerator between the governments of the three signatory nations by accelerating the development and application of critical technologies in the hands of their servicemen and women. It is a trilateral agreement that is bringing three other joined "trilateral" in each of the three nations: between governments, research organizations, and companies—including tech firms outside the traditional defense sector. AUKUS is deeply complementary to the QUAD (an alliance of four countries, Australia, the USA, Japan, and India, formed in 2007), and a foundational contribution to a free, open, and inclusive Indo-Pacific. While AUKUS focuses on security issues, QUAD discusses diplomatic and global issues, including the COVID-19 situation, vaccines, technological innovation, supply chain resilience, and climate change.

LITERATURE REVIEW

Several nations have implemented UHC-inspired health reforms, and UHC has been identified as one of the new SDGs (Horton and Das, 2015). Moreover, regardless of their financial ability to pay, everyone obtains the healthcare they require without undue financial hardship (Boerma et al., 2014). Investing in more comprehensive UHC and primary care can improve population health and reduce health disparities. Trade-offs do occur between health policy objectives. Healthcare technologies, policies, and resources should be subjected to distributional analysis (Cookson et al., 2021). Particularly, with the United Nations SDGs 2030, Goal 3, "Indicator 3.8.1": Coverage of essential health services and "Indicator 3.8.2": Proportion of population with large household expenditures on health as a share of total household expenditure or income are vital areas of focus (UN-SDG, 2019). Measuring progress toward UHC, thus, entails keeping track of both the service coverage and financial security components of UHC. An earlier study (Hogan et al., 2018) on summarizing national levels of service coverage to track progress toward UHC either concentrated on specific regions or relied on mortality-based metrics that are imprecisely recorded in the majority of developing nations. The monitoring framework for SDGs calls for the creation of an index of critical service coverage to track progress toward SDG goal 3.8 on universal healthcare across nations (Hogan et al., 2018).

However, except for two studies (Wagstaff et al., 2015, 2016), works have evaluated each dimension of UHC separately. Such studies, as noted by Hogan et al. (2018), Wagstaff et al. (2018a), and possibly misleading (McPake BI., 2018), are potentially misleading as nations may perform well on one UHC component but not the other. Low out-of-pocket expenditure (OOPS) on health might indicate that individuals are not getting the treatments they require or they are receiving these services but are not paying for them out-of-pocket. Furthermore, a high level of use of health services may or may not be related to a high degree of out-of-pocket cost.

"Machine learning is the most visible expression of AI and the newest development area in digital technology, promises to accomplish more with less and might be the catalyst for such a shift (PubMed Central (PMC), 2018). However, the nature and scope of this commitment has [sic] not been thoroughly evaluated". "To overcome these problems and attain universal health coverage (UHC) by 2030, a fundamental restructuring of health systems is necessary".

On many occasions, health and healthcare are often linked, the former as a direct function of the latter. However, attaining the level of healthcare services that guarantee optimal health is a mirage for most countries. Though health is a state subject that requires the government to ensure the delivery of healthcare to the population, the reality of UHC remains an unrealized dream. The situation in the Indian context is complicated by the enormous population and the prevalence of infectious and noncommunicable diseases burden. Additionally, the issues of gender equity, the predominance of the private health sector for secondary and tertiary care, maldistribution of trained human resources, and economic factors complicate attaining desired levels of UHC. Policy requirements at the national and state level need to be guided by research to identify the core determinants that have a bearing on UHC (Singh, 2013).

Health indicators, such as maternal mortality ratio, infant mortality rate, and under-five mortality rates, are sensitive to factors related to healthcare delivery systems. However, morbidity indicators reflect UHC more realistically as mortality is not an outcome of several diseases, especially chronic illness. Across the globe, governments are trying to ensure optimal access and affordable healthcare for populations. The costs of healthcare are rising in the wake of modern and diagnostic advances in healthcare. Though primary healthcare is essential to ensure the health and wellbeing of the masses, the availability of secondary and tertiary curative and rehabilitative networks completes the circle of healthcare. With the emergence of mental health issues as an additional burden of morbidity that requires early diagnosis and appropriate management, healthcare systems are getting overwhelmed. In this context, policymakers need to identify modifiable determinants to ensure universal healthcare and promulgate affirmative actions toward achieving the same. The sustenance of interventions needs to be considered for long-term benefits to the system. A multi-sectoral approach with the cooperation and involvement of non-health players is essential to achieve universal healthcare for the population (Kumar, 2020).

Proposed Framework

The suggested conceptual framework is an output-input framework, as depicted in **Figure 1**. As stated in earlier sections, UN SDG Target 3.8-achieving UHC is a primary objective, which includes financial risk protection, easy accessibility to most essential health services, access to adequate quality, affordable, most essential medications, and vaccinations for everyone. It is essential to reach everyone who requires health-related services (including health services, medicines, and other resources). Healthcare services must be served without spending out-of-pocket and without witnessing financial hardships. To achieve this, two indicators are identified under 3.8—namely, 3.8.1 and 3.8.2. The 3.8.1 indicator focuses on UHC, and the 3.8.2 indicator focuses significantly on healthcare-related financial hardship/burden on patients. The two indicators in 3.8 primarily represent healthcare service coverage and financial protection. Reproductive facilities, newborn care, child healthcare, handling of medication for infectious diseases, and treatment of communicable/noncommunicable diseases are covered by essential health coverage. These are the categories that represent the most disadvantaged populations. The indicators used to measure the effectiveness of implemented policies are based on a scale of 0–100. This unit of measurement has no unit. These indicators are derived from 14 various healthcare coverage factors. Thus, in the framework, the purpose is to predict UHC (the output Y_{it}) in different blocks, and how they are influenced by various factors (the inputs X_{it} and the control factors Z_{it}).

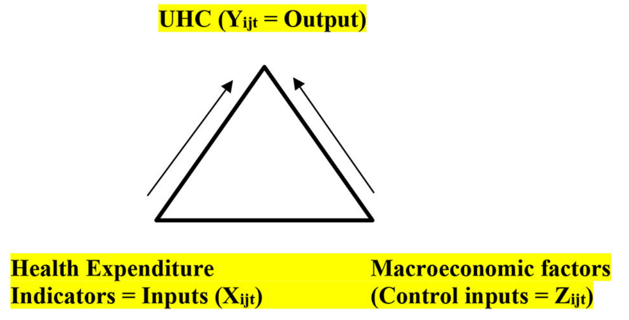

FIGURE 1 | Conceptual framework. Input-output relation of universal health coverage (UHC) with health expenditure and macroeconomic factors.

Figure 1 succinctly encompasses the input-output analysis to address the research objectives. The input and control input factors are detailed in **Table 1**.

The framework is empirically analyzed using the following traditional OLS and ML specifications:

Empirical model (traditional OLS):

$$Y_{jjt} = \alpha_{ijt} + \beta_{ijt}\sum\sum\sum X_{ijt_{+}}\pi_{ijt}\sum\sum\sum Z_{ijt} + \text{Error}_{ijt} \quad (1)$$

where Y_{ijt} = output = UHC index service coverage for countries in the three blocks j and $t = 2017, 2019$.

X_{ijt} = Set of healthcare indicators inputs for countries in the three blocks j and $t = 2017, 2019$.

Z_{ijt} = Set of macro factors such as GDP (2019 constant US$), inflation, and size of the country represented by population for countries in the three blocks j and $t = 2017, 2019$.

J = 14 economies grouped into three economic blocks (represented by indicators 1, 2, 3), where 1 represents the BRICS block (five developing economies): Brazil, Russia, India, China, and South Africa); 2 represents the GCC block (six developing oil-rich economies: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE); 3 represents the AUKUS block (three developed economies: Australia, the UK, and the USA); and t = time

TABLE 1 | Details of Output (Y_{ijt}) and Inputs (X_{ijt} and Z_{ijt}).

Y/X_i	Variable name
Y	Universal Health Coverage
X_1	Current Health Expenditure (CHE) as % Gross Domestic Product (GDP)
X_2	Current Health Expenditure (CHE) per Capita in US$
X_3	Voluntary Health Insurance (VHI) as % of Current Health Expenditure (CHE)
X_4	Out-of-pocket (OOPS) as % of Current Health Expenditure (CHE)
X_5	Out-of-Pocket Expenditure (OOPS) per Capita in US$
X_6	Compulsory Financing Arrangements (CFA) as % of Current Health Expenditure (CHE)
X_7	Government Financing Arrangements (GFA) as % of Current Health Expenditure (CHE)
X_9	Voluntary Financing Arrangements (VFA) as % of Current Health Expenditure (CHE)
X_{17}	Current Health Expenditure (CHE)
X_{18}	Domestic General Government Health Expenditure (GGHE-D)
X_{19}	Domestic Private Health Expenditure (PVT-D)
Macro factors	
Z_1	GDP-constant 2019 US$ reflecting the magnitude of the country's economy in year t
Z_2	Inflation reflecting purchase power parity of the country in year t
Z_3	Population reflecting size of the country in year t

indicator (2017, 2019) years where full and consistent data are available for all the 14 countries.

Data

The indicators above are collected from the WHO Global Health Indicator database and UHC periodical surveys of 2017 and 2019 for the 14 countries stated earlier (survey data were not complete for all 14 countries for 2005 and 2016 and, hence, were not wholly included in the analysis). The following hypotheses are tested in both OLS and ML specifications.

Data Limitations

Because of data constraints, not all tracer indicators used to calculate the UHC index are direct service coverage measurements. The chosen tracer indicators indicate the broad range of primary healthcare required for progress toward UHC; they should not be taken as a suggested basket of services. The WHO data were curated with the following attributes.

1. Since UHC data are available for 2017 and 2019, we have focused on these 2 years' indicators and macro factors. Therefore, all years before 2017 were excluded. Wherever the information for 2017 or 2019 was missing, the data were extrapolated by taking the average of the survey data from the prior 5 years.
2. Furthermore, there were no granular data in specific healthcare categories in developed countries. Therefore, these components were excluded from the data set.

ML Methodology

Since we have only 2 years of UHC and X_i data for all block countries, applying traditional OLS will be less valuable as the degree of freedom will be very low[2]. Hence, we use ML algorithms similar to regression in concept, viz., "Random Forest regressor," a Decision Tree method.

Overview of Random Forest Tree Method

Random Forest is an ensemble learning technique for classification, regression, and other problems that are trained with many decision trees. Because the decision tree is a simple method, a single tree may not be sufficient for the ML model to acquire its features. On the other hand, Random Forest is a "Tree"-based algorithm that produces decisions by blending the characteristics of many decision trees. As a result, it is possible to characterize it as a "Forest" of trees, hence the term "Random Forest." This approach is a forest of "Randomly Created Decision Trees," as the name implies.

Overfitting is a crucial disadvantage of the decision tree approach. However, this difficulty may be minimized by employing the Random Forest regression instead of the decision tree regression. Furthermore, the Random Forest approach is more robust and speedier than traditional regression models. To summarize, the Random Forest algorithm combines the outcomes of many decision trees to get the final result.

A Random Forest is an ensemble approach in AI that performs prediction and classification by collating several trees using bootstrap (sometimes referred to as bagging). Instead of considering one decision tree, the main idea is to aggregate numerous trees to decide the outcome.

We randomly choose rows and features from the data set to create sample data sets for each model. This section is known as bootstrap. We must approach the Random Forest regression technique in the same way as we would any other ML technique:

- Create a specific query or data set and work with the source to determine the relevant data.
- Ensure that the data are in an easily accessible format. Otherwise, convert them to the appropriate forum.
- Specify any apparent abnormalities or missing data points necessary to obtain the relevant data.
- Develop an ML model.
- Determine the baseline model you wish to accomplish.
- Train the ML model using the data.
- Using the test data, provide insights into the model.
- Now compare the performance metrics of the test data with the model's projected data.
- If it does not meet researchers' expectations, we may improve the model by dating our data or using another data modeling approach.
- Interpret the data at this point.
- At this point, analyze the data gathered by researchers and report accordingly.

[2]This was verified by the OLS model results but not reported here for brevity.

TABLE 2 | Basic Random Forest-Based feature importance for UHC coverage covering all the three blocks.

Feature name	Variables name	Random forest feature (RFF)	RFF importance
X5	Out-of-Pocket Expenditure (OOPS) per Capita in US$	0.23952136	1
X19	Domestic Private Health Expenditure (PVT-D)	0.189957	2
X18	Domestic General Government Health Expenditure (GGHE-D)	0.1155865	3
X2	Current Health Expenditure (CHE) per Capita in US$	0.09970508	4
X17	Current Health Expenditure (CHE)	0.08736607	5
Z1	GDP-constant 2019 US$	0.06472806	6
X1	Current Health Expenditure (CHE) as % Gross Domestic Product (GDP)	0.0646806	7
X6	Compulsory Financing Arrangements (CFA) as % of Current Health Expenditure (CHE)	0.03737473	8
X7	Government Financing Arrangements (GFA) as % of Current Health Expenditure (CHE)	0.03265779	9
Z3	Population	0.02063635	10
X9	Voluntary Financing Arrangements (VFA) as % of Current Health Expenditure (CHE)	0.01583275	11
X3	Voluntary Health Insurance (VHI) as % of Current Health Expenditure (CHE)	0.01494308	12
X4	Out-of-pocket (OOPS) as % of Current Health Expenditure (CHE)	0.01103154	13
Z2	Inflation	0.0059791	14

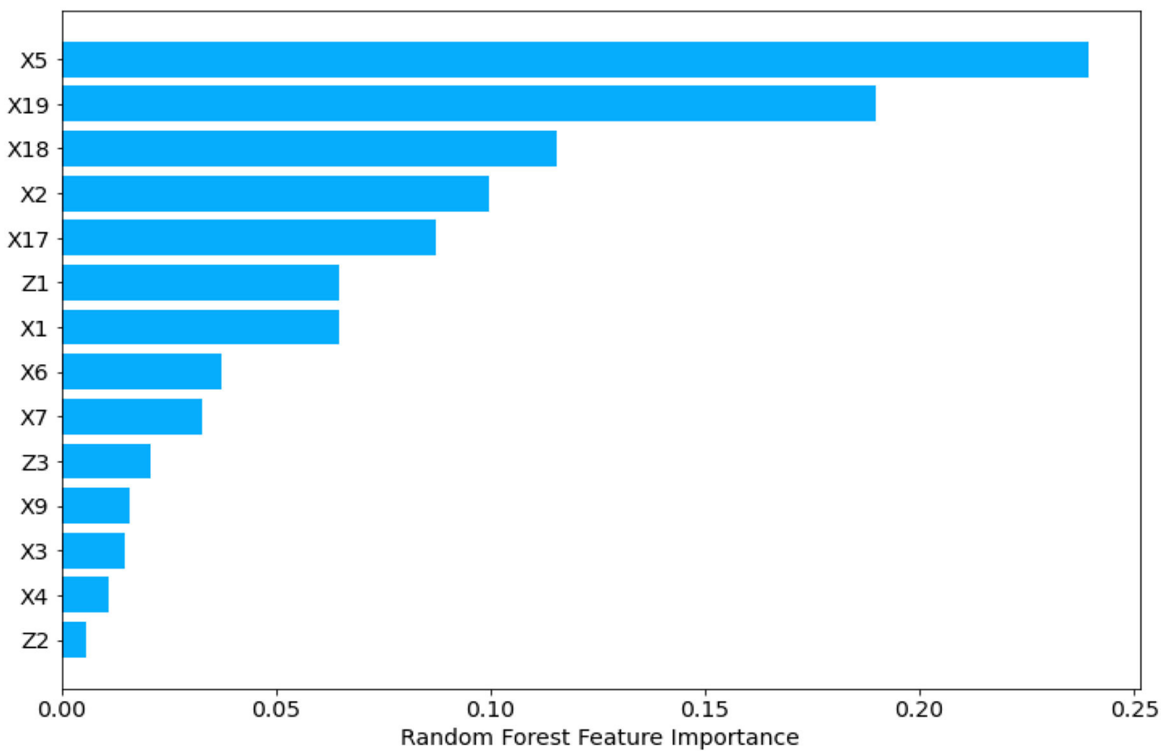

FIGURE 2 | Random Forest feature importance in UHC for all three economic blocks.

RESULTS

Radom Forest Tree Results

Table 2 shows the features that influence UHC after applying the abovementioned technique.

For all the blocks, UHC is impacted by:

- OOPS per Capita in US$ with the importance of 23.95% *(General Hypothesis 2 is validated)*.
- PVT-D with the importance of 18.99%.
- Domestic government health expenditure (GGHE-D) with the importance of 11.56%.
- CHE per Capita in US$ with the importance of 9.97%.
- CHE with the importance of 8.74%.
- GDP-constant 2019 US$ (magnitude of the economy) with the importance of 6.47%.

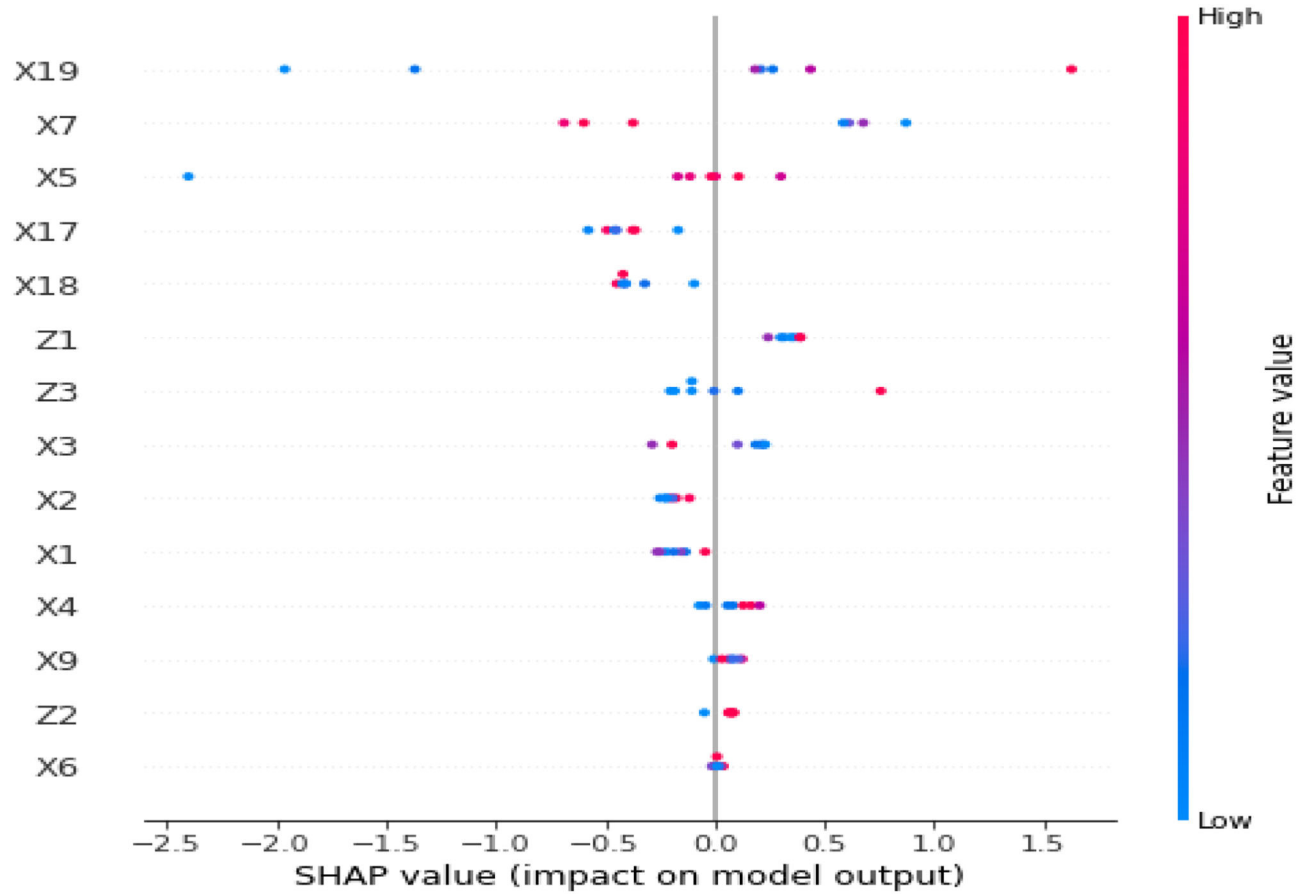

FIGURE 3 | SHapley Additive exPlanations (SHAP) value for UHC prediction in all the blocks.

- CHE as a percentage of GDP is 6.47% *(General Hypothesis 1 is validated).*
- Compulsory Financing Arrangements (CFA) as a percentage of CHE with a weight of 3.74% *(General Hypothesis 3 is validated).*
- Government Financing Arrangements (GFA) as a percentage of CHE with a weight of 3.27% *(General Hypothesis 4 is validated).*
- Population (density of human capital in the economy) with the importance of 2.1%.
- Voluntary Financing Arrangements (VFA) as a percentage of CHE with a value of 1.58% *(General Hypothesis 5 is validated).*
- Voluntary health insurance (VHI) as % of CHE with the importance of 1.49%.
- OOPS expenditure as a percentage of CHE with a significance of 1.1%.
- Inflation with the significance of 0.006%.
- This validates our specific hypotheses that the importance of each input and control factor varies across the three blocks for UHC prediction.
- The Random Forest-based results depicted in **Table 2** are graphically illustrated for all the blocks, and the same is shown in **Figure 2**.

Shapley Additive Explanations to Understand the Results Produced by Random Forest Techniques

SHapley Additive exPlanations (SHAP) is most likely at the cutting edge of ML explainability. Lundberg (2017) initially released this technique, which is an excellent approach to reverse engineer the output of any prediction algorithm. SHAP values are utilized when researchers have a sophisticated model (a gradient boosting, a neural network, or anything that accepts some characteristics as the input and makes predictions as the output) and understand the model's decisions.

SHapley Additive exPlanations values are derived from Shapley values, a game theory term. For example, consider the following scenario: we have a predictive model; the "game" and the "players." SHAP quantifies the contribution of each feature to the model's prediction. It is critical to emphasize that a "game" refers to a single observation, one observation per game. SHAP is all about a prediction model's local interpretability. The SHAP value plot can further show the positive and negative relationships of the predictors (X_i) related to the target variable (in our case, UHC). This graphic plot is

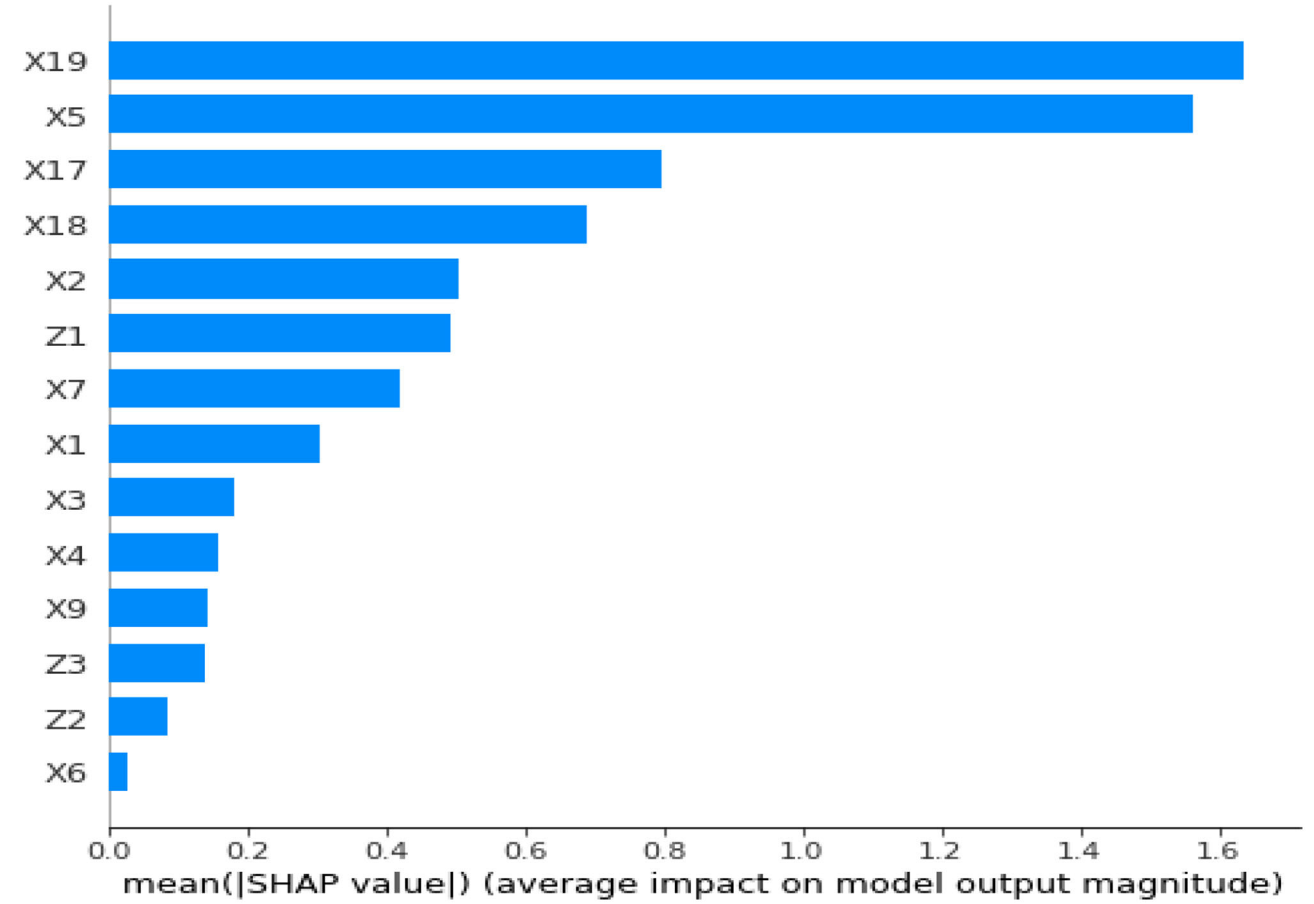

FIGURE 4 | Mean SHAP values of predictors in UHC in all the blocks.

constructed using all of the dots in the train data. It displays the following data:

Importance of feature: Variables are ordered descending.

Impact: The horizontal placement indicates whether the value's influence is related to a higher or lower forecast.

Original price: The color indicates whether the variable of that observation is high (in red) or low (in blue).

Figure 3 depicts the SHAP values for all blocks in our UHC forecast. The red hue represents the "high" effect.

We can quantify the contribution of the input characteristics to the individual predictions by using the SHAP values in the model explanation. The *x*-axis in this chart represents the SHAP value, while the *y*-axis contains all of the characteristics. Each point on the graph represents a single SHAP value for a prediction and feature. The color red denotes a greater value for a characteristic. The blue color denotes a lower value for a characteristic. Based on the distribution of the red and blue dots, we can obtain a basic sense of the influence of characteristics on directionality. We shall practically verify the results of the SHAP values shown in **Figure 3**. In this graph, based on the previous explanation, we can make the following interpretations, for example:

- The higher the value of X19 [domestic private health expenditure (PVT-D)], the higher the value of UHC.
- It can be interpreted from the feature values of X5 (OOPS) to have a negative bearing on the full realization of the optimal UHC potential for a given country.

Similarly, with the help of the SHAP visualization, one can interpret the impact of feature values (either positive or negative) on the predictive variable (in our case, high or low UHC). **Figure 4** shows the mean SHAP values for UHC prediction in all the blocks.

Figure 4 shows a slight shift in the percentage relevance of UHC compared to **Figure 2**.

Comparing the Error Component in Terms of Root Mean Square Error

The results in **Figure 5** illustrate the root mean square error (RMSE) values of the methods used in this study. We have

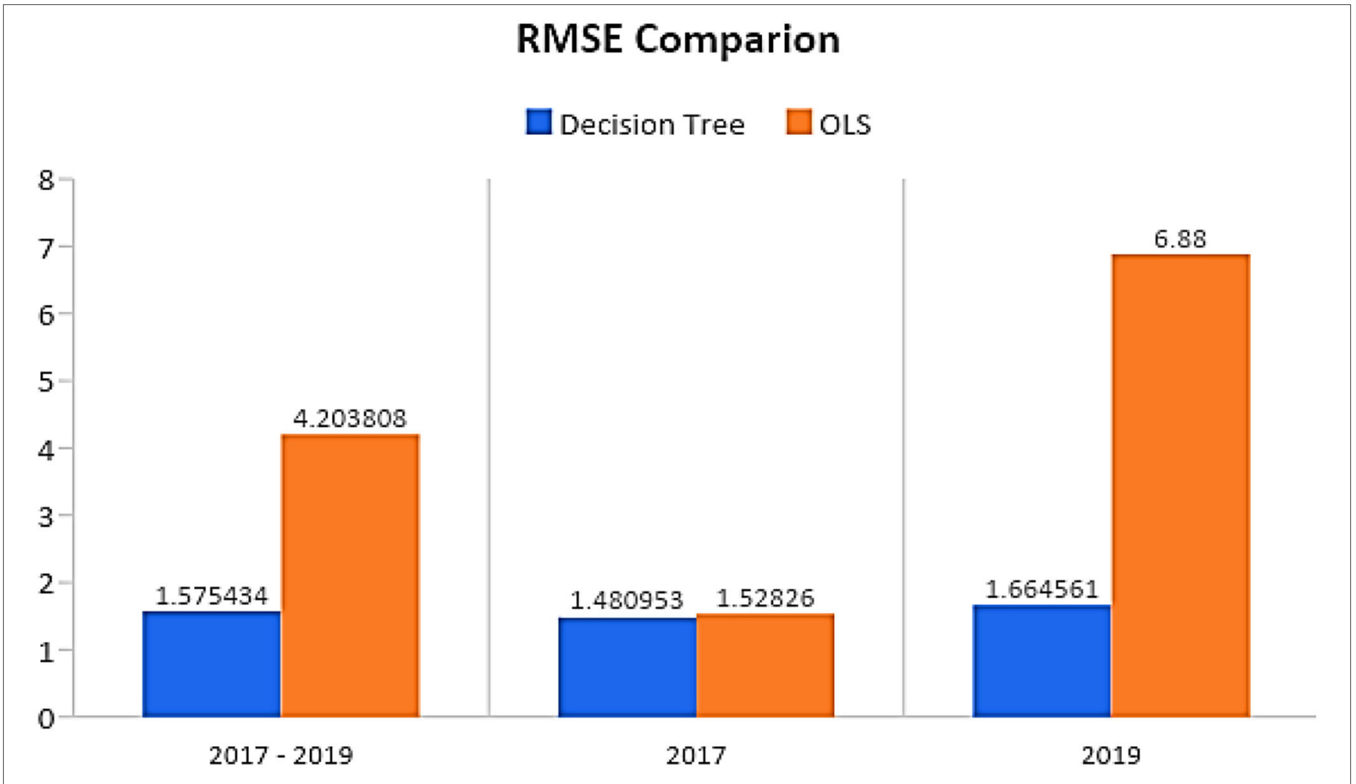

FIGURE 5 | Root mean square error (RMSE) comparison between Random Forest Decision Tree ML method and ordinary least square (OLS).

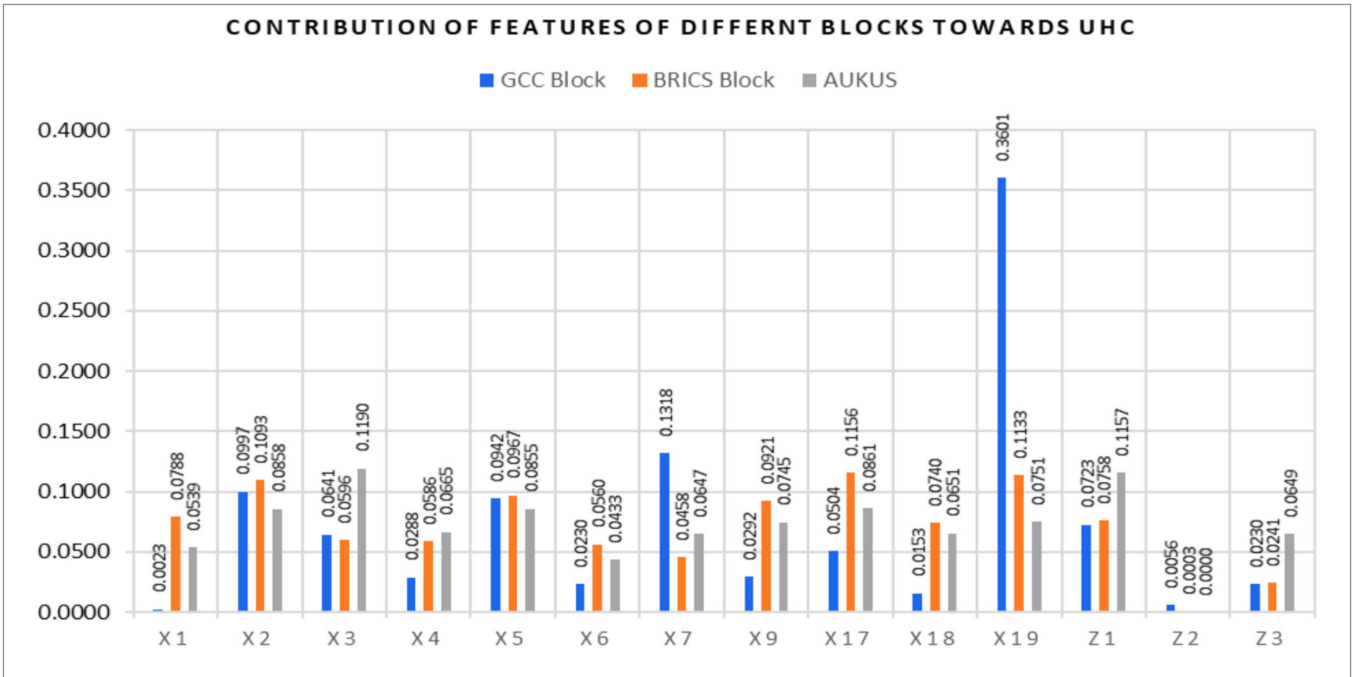

FIGURE 6 | Contribution of the features for UHC in each block.

used OLS and Random Forest-based algorithms for UHC prediction. This validates our *general Hypothesis 6 that the ML technique is more appropriate for predicting UHC than the traditional OLS technique*. The result illustrated in the graph firmly conveys that Random Forest performs has superior performance to the traditional OLS model shown. Furthermore,

TABLE 3 | Less developed BRICS economic block predictors.

X17	Current Health Expenditure (CHE) Constant 2019 US$
X19	Domestic Private Health Expenditure (PVT-D)
X2	Current Health Expenditure (CHE) per Capita in US$
X9	Voluntary Financing Arrangements (VFA) as % of Current Health Expenditure (CHE)
X5	Out-of-Pocket Expenditure (OOPS) per Capita in US$
X1	Current Health Expenditure (CHE) as % Gross Domestic Product (GDP)
X18	Domestic General Government Health Expenditure (GGHE-D)
Z1	GDP-constant 2019 US$ (reflecting richness of the block)
X3	Voluntary Health Insurance (VHI) as % of Current Health Expenditure (CHE)
X4	Out-of-pocket (OOPS) as % of Current Health Expenditure (CHE)
X6	Compulsory Financing Arrangements (CFA) as % of Current Health Expenditure (CHE)
X7	Government Financing Arrangements (GFA) as % of Current Health Expenditure (CHE)
Z3	Population (Size of the economy)

The predictors are arranged in decreasing order of importance for UHC coverage.

TABLE 4 | Oil-rich GCC economic blocks had the predictors.

X19	Domestic Private Health Expenditure (PVT-D)
X7	Government Financing Arrangements (GFA) as % of Current Health Expenditure (CHE)
X2	Current Health Expenditure (CHE) per Capita in US$
X5	Out-of-Pocket Expenditure (OOPS) per Capita in US$
Z1	GDP-constant 2019 US$ (reflecting richness of the block)
X3	Voluntary Health Insurance (VHI) as % of Current Health Expenditure (CHE)
X17	Current Health Expenditure (CHE) Constant 2019 US$
X9	Voluntary Financing Arrangements (VFA) as % of Current Health Expenditure (CHE)
X4	Out-of-pocket (OOPS) as % of Current Health Expenditure (CHE)
Z3	Population (Size of the economy in the block)
X6	Compulsory Financing Arrangements (CFA) as % of Current Health Expenditure (CHE)
X18	Domestic General Government Health Expenditure (GGHE-D)
Z2	Inflation

Predictors are arranged in decreasing order of importance for UHC coverage.

Random Forest predictions have less residual than the OLS model.

In **Figure 6**, the less developed BRICS economic block predictors are shown in **Table 3**. The predictors are arranged in decreasing order of importance for UHC. This validates our *specific hypotheses that the importance of each input and control factor varies across the three blocks, and the impact factors (synoptic weights in the ML model) also differ across the blocks for predicting UHC.*

Inflation was not a key feature in the BRICS block to expand UHC. The BRICS economies must expand proactively health financing through the private sector, insurance sector, and government sector from the policy perspective. There is an incentive for individual households to increase their OOPS for getting full health coverage. The economy's health coverage strategy was undertaken from the feature importance in the oil-rich GCC block discussed below. Oil-rich GCC economic blocks had the predictors, as shown in **Table 4**. The predictors are arranged in decreasing order of importance for UHC.

Oil-rich economies of the GCC are way ahead of less developed BRICS economies in expanding UHC by promoting private, compulsory, voluntary, insurance, and government participation. It also makes sense as 80% of the GCC population are expats and get permission to work as a resident in these economies. The minimum requirement is to have health insurance, either from private insurers or from their contribution as a requirement for obtaining a work permit. Are these health service measures on par with the developed economies in AUKUS? Let us examine this in the next section. The developed AUKUS economic block had the predictors in decreasing order of importance for UHC in **Table 5**.

Due to their highly developed status, productive resources (both physical, financial, and technological), and best health service strategies implemented by these economies, UHC is the highest in the AUKUS block compared to the BRICS and GCC blocks. The GCC has leveraged the best practices of the AUKUS to expand UHC in their economies. The abovementioned interblock analysis concludes that the economies of the BRICS should proactively follow health coverage strategies and financing arrangements prevalent in the GCC and AUKUS blocks.

TABLE 5 | Developed AUKUS economic block had the predictors in decreasing order of importance for UHC coverage.

X3	Voluntary Health Insurance (VHI) as % of Current Health Expenditure (CHE)
Z1	GDP-constant 2019 US$ (reflecting richness of the block)
X5	Out-of-Pocket Expenditure (OOPS) per Capita in US$
X2	Current Health Expenditure (CHE) per Capita in US$
X17	Current Health Expenditure (CHE) Constant 2019 US$
X19	Domestic Private Health Expenditure (PVT-D)
Z3	Population (Size of the economy in the block)
X18	Domestic General Government Health Expenditure (GGHE-D)
X7	Government Financing Arrangements (GFA) as % of Current Health Expenditure (CHE)
X4	Out-of-pocket (OOPS) as % of Current Health Expenditure (CHE)
X1	Current Health Expenditure (CHE) as % Gross Domestic Product (GDP)
X6	Compulsory Financing Arrangements (CFA) as % of Current Health Expenditure (CHE)

It is demonstrated that the current study on UHC with respect to the three economic blocks has identified the inter- and intra-block significant (and less significant) factors. The identified factors will act as a feedback input to fine-tune UHC-related policy modifications. The decision for improvement can be informed. The focus of this research is 2-fold: to identify the critical UHC-related inter- and intra-block features and to obtain the superiority of AI ML-oriented techniques in relation to traditional Statistical bound techniques. The implemented decision tree models have shown that the prediction of UHC can be significantly improved with AI ML methods. From the perspective of the Random Forest algorithm, we are able to derive important features for inter-/intra-block UHC calculation and residual prediction calculation. The results are sustainable up to the current time, considering the advances in the analytical domain.

LIMITATIONS

Some limitations and concerns with the index, both at the international and national levels, must be resolved in future revisions before it can be considered complete. While defining the tracer indicators, it was discovered that there was a data scarcity for the global measurements of healthcare coverage (SDG indicators 3.8.1 and 3.8.2). However, the goal was to select measures of effective service coverage, as most of the currently available index indicators measure contact coverage rather than effective service coverage. As a result, coverage measures were not selected as tracer indicators for several essential health sectors. For example, meaningful indicators of coverage of interventions for noncommunicable illnesses, mental health, injuries, and emergencies are currently scarce in most countries. In these areas, proxy measures of service coverage were used in place of coverage indicators, such as data on service capacity or health status, to determine whether services were being provided.

DIRECTIONS FOR FUTURE RESEARCH

An increased effort in data collection, particularly national health examination surveys that measure the service coverage across the different domains of health, and the amount of money spent on health by households, will significantly improve countries' ability to track progress toward UHC and to complete sub-national assessments of UHC, which are likely to be the most useful ones to national policymakers in the long run. Future research can exploit these surveys efficiently toward SDG 3.8.1 3.8.2 and UHC issues.

CONCLUSION

Policymakers must identify the core modifiable determinants of UHC for framing appropriate policies to ensure optimal coverage. The steps that need to be taken to alter health spending require a complex set of strategies and the involvement of several sectors. Increasing healthcare spending as a higher proportion of GDP is essential to tackle the economic determinants of UHC. To attain the target eight of SDG three, it is imperative for the healthcare providers to identify the cost centers of healthcare and address them effectively. PVT-D, OOPS per Capita in US$, and VHI as a percentage of CHE are the key factors influencing UHC across the blocks, according to the integrated models of the three economic blocks. Federal funding of comprehensive healthcare is highly challenging due to several complex features of individual healthcare systems worldwide. Largely, policies that address the issues of enhancing healthcare financing through the contribution of individuals and with the support of the federal funding structure show promise for the future.

Additionally, efforts toward containing the private expenditure for health through enhanced preventive primary healthcare would benefit UHC across different spectrums and geographies. In addition, the cost(s) incurred for primary preventive care are less than those of tertiary curative interventions. The preventive paradox makes the costs of curing existing morbidities (secondary prevention strategies) a considerable challenge as compared to primary prevention to restrict the emergence of the diseases in the first place. In this context, it is proposed that sufficient emphasis and funding allocations are made in the policies for preventive, curative, and rehabilitative healthcare services to achieve UHC.

AUTHOR'S NOTE

Economic block is formed by a set of countries with common long-term and immediate goals. These countries normally engage in international trades with each other and other associations related to their growth.

Brazil, Russia, India, China, and South Africa compose the BRICS economic bloc, which is made up of emerging economic powers and political influencers. These countries account for 40 percent of the world's population and 20 percent of its gross domestic output (GDP). The BRICS group's mission is to promote peace, security, development, and collaboration. The BRICS countries argue for five universal principles: sovereignty, unity, independence, territorial integrity, non-aggression, and equality. These five nations do have certain characteristics: they are all huge, populous, and varied, with numerous ethnic, socioeconomic, and - in some cases - religious differences. They share similar traits with a number of other nations, including Indonesia, Nigeria, and Pakistan, who have made less progress toward UHC but may benefit from the BRICS' experiences. There is little question that collaboration and shared learning are essential in the promotion of UHC (McKee et al., 2014).

Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates comprise the Gulf Cooperation Council (GCC) (UAE).

The formation of AUKUS - a "enhanced trilateral security partnership" involving Australia, the United Kingdom, and the United States that will be launched in September 2021 - has fuelled the already growing momentum toward monoliteral cooperation in the Indo-Pacific in order to "meet the challenges of the twenty-first century." The deal has broad objectives, including encouraging more information and technology exchange, integrating security and defence-related research, technology, industrial bases, and supply chains, and improving the three countries' combined capabilities and interoperability. Despite being exclusive to the three Anglo partners, the grouping has the potential to provide enormous value to the Indo-Pacific regional security architecture (Jagannath, 2022).

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frai.2022.887225/full#supplementary-material

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REVIEW
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Detection of COVID-19 Using Deep Learning Techniques and Cost Effectiveness Evaluation: A Survey

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Graphical-design-based symptomatic techniques in pandemics perform a quintessential purpose in screening hit causes that comparatively render better outcomes amongst the principal radioscopy mechanisms in recognizing and diagnosing COVID-19 cases. The deep learning paradigm has been applied vastly to investigate radiographic images such as Chest X-Rays (CXR) and CT scan images. These radiographic images are rich in information such as patterns and clusters like structures, which are evident in conformance and detection of COVID-19 like pandemics. This paper aims to comprehensively study and analyze detection methodology based on Deep learning techniques for COVID-19 diagnosis. Deep learning technology is a good, practical, and affordable modality that can be deemed a reliable technique for adequately diagnosing the COVID-19 virus. Furthermore, the research determines the potential to enhance image character through artificial intelligence and distinguishes the most inexpensive and most trustworthy imaging method to anticipate dreadful viruses. This paper further discusses the cost-effectiveness of the surveyed methods for detecting COVID-19, in contrast with the other methods. Several finance-related aspects of COVID-19 detection effectiveness of different methods used for COVID-19 detection have been discussed. Overall, this study presents an overview of COVID-19 detection using deep learning methods and their cost-effectiveness and financial implications from the perspective of insurance claim settlement.

Keywords: COVID-19 diagnosis, deep learning, artificial intelligence, chest X-ray, chest CT, COVID financial management, insurance

INTRODUCTION

Coronavirus is a zoonotic virus and an RNA virus in the family Coronaviridae, wherein these zoonotic diseases are infectious diseases caused by the transmission of pathogens from animals to humans. It is a class of viruses that belong to respiratory contagion. The virus is entitled Coronavirus because of the crown-like spikes on the virus's outer covering. Corona is a sort of infection that creates respiratory ailments in humans (Darapaneni et al., 2020).

The various deadly coronaviruses discovered to date are,

1. *SARS-CoV* induces *severe acute respiratory syndrome (SARS)*
2. *MERS-CoV* which causes *Middle East respiratory syndrome (MERS)*
3. *SARS-CoV2* which is novel coronavirus that causes *COVID-19*.

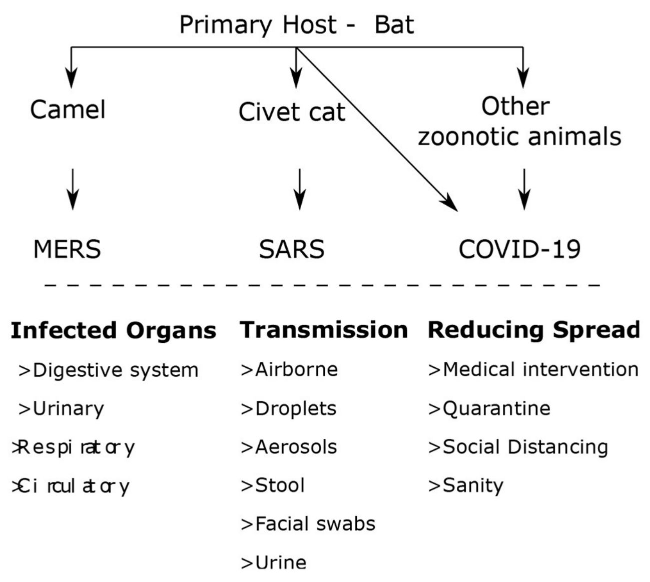

FIGURE 1 | Transmission of the SARS-COV (Darapaneni et al., 2020).

TABLE 1 | COVID-19 cases and fatalities by region (Dhama et al., 2020, see text footnote 4).

Region	Total cases	Total deaths
South America	37,737,608	1,151,181
North America	44,548,923	710,757
European Union and the UK	45,509,611	896,885
Other Europe	12,406,547	179,154
Central America	5,679,357	316,053
Russia and Central Asia	10,044,890	239,175
Middle East	13,169,156	195,989
Caribbean	1,833,102	20,779
South Asia	38,017,617	533,859
Oceania and islands in East Asia	8,661,338	200,334
North Africa	2,498,484	66,730
Sub-Saharan Africa	5,786,014	143,124
East Asia	5,920,734	88,922
Totals	231,813,381	4,742,942

Novel Coronavirus (COVID-19) originated in bats and was transmitted to humans in December 2019 by an unknown animal in Wuhan, China (El Gannour et al., 2020). People who feel high temperatures, coughing, aching throats, tiredness, muscle aches, throat pain, and difficulty breathing could be affected by this virus (Thepade and Jadhav, 2020). The World Health Organization declared COVID-19 a Public Health Emergency of International Concern on January 30, 2020, and it was declared a global pandemic on March 11, 2020.

Figure 1 demonstrates the transmission of the severe acute respiratory syndrome coronavirus (SARS-CoV). SARS-CoV-2 strains are classified into four genera: alpha, beta, gamma, and delta. However, the genera alpha and beta descended from bats, whereas gamma and delta descended from birds and peccary gene provision. For SARS and MERS, civet cats and camels act as the proprietors. The most common symptom associated with the COVID-19 dreadful disease is Pneumonia, which appears to be the most common indication of contamination, along with other primary symptoms such as fever, cold, body pain, sore throat, and epistaxis (Darapaneni et al., 2020).

The total number of cases in the first wave till June 2020 real cases are 8,708,008, while the inclusive estimate of mortality is 461,715 (WHO Statistics). However, the severity of COVID-19 demonstrates the second wave total number of instances till June 1, 2021. As a result, the absolute number of verified cases is 171,782,908, while the cumulative mortality estimate is 3,698,621[1,2]

According to WHO, there were 33,766,707 confirmed cases of COVID-19 in India between January 3, 2020, and October 1, 2021, with 448,339 fatalities. 870,708,636 vaccine doses were delivered as of September 27, 2021[3] The worldwide COVID-19 cases and fatalities by region, in absolute numbers, as of September 27, 2021, are shown in **Table 1** (Dhama et al., 2020)[4] These regions are adapted according to the World Bank. The worldwide COVID-19 cases and fatalities were reported by age and gender between 30 December 2019 and 27 September 2021, which is summarized in **Figure 2** (see text footnote 1).

The COVID-19 crisis has created a social, economic, and wellness upheaval. Lockdowns have resulted in people losing their employment. These things have created tremendous pressure on people's mental health and badly affected them physiologically. The facility of online working has helped the industry survive by working from home. However, those industries that have been badly affected involve physical work like labor, technicians, etc. People who belong to poor-class family-like labor, street workers, are badly affected by the lockdowns. The lockdown has enormous negative consequences, particularly for the economy.

In terms of vulnerability, millions of people in India are being dragged into poverty, food insecurity, health, and online education availability issues. From the other perspective, COVID-19 pandemic has given space to many innovations. An Automated System to Limit COVID-19 Using Facial Mask Detection in Smart City Network has been proposed by Rahman et al. (2020). Scalable Telehealth Services to Combat Novel Coronavirus Pandemic was successfully demonstrated by Ullah et al. (2021). Wearable technology to assist patients infected with novel Coronavirus has been implemented by Islam M. et al. (2020). Breathing Aid Devices to Support Novel Coronavirus Infected Patients demonstrated by Islam et al. (2020).

[1]Who coronavirus (COVID-19) dashboard. https://COVID19.who.int/
[2]Who COVID-19 explorer. https://worldhealthorg.shinyapps.io/COVID
[3]India: Who coronavirus disease (COVID-19) dashboard with vaccination data. https://COVID19.who.int/region/searo/country/in
[4]http://www.sirm.org/category/senza-categoria/COVID-19/

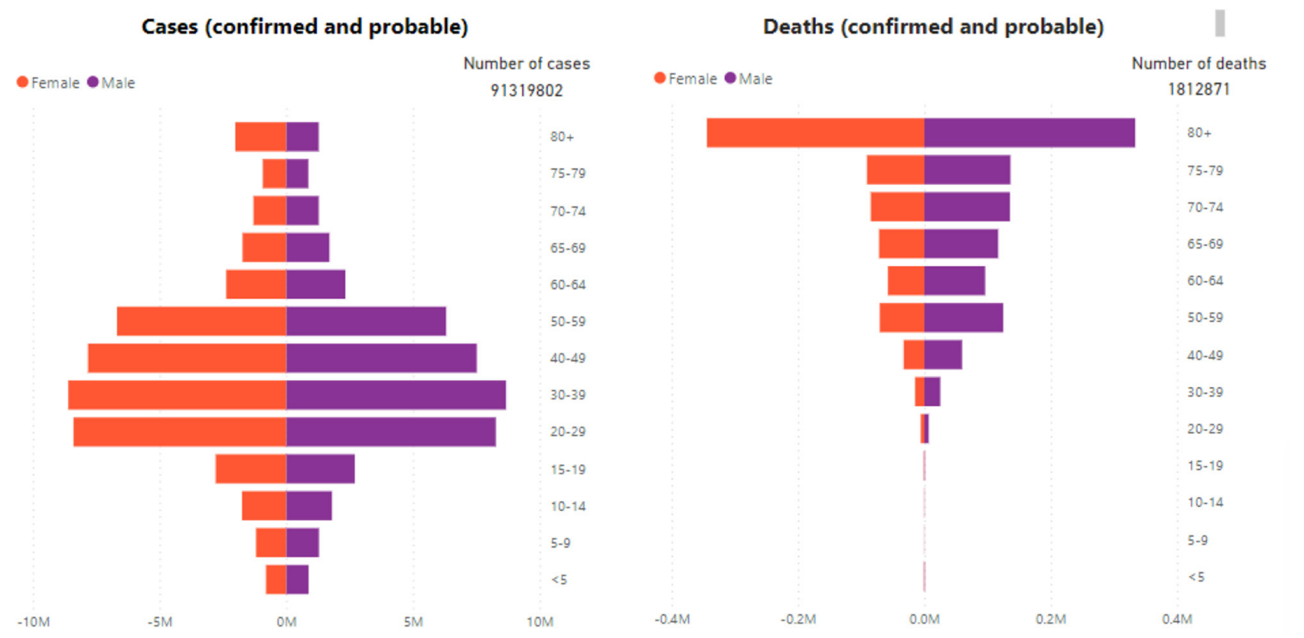

FIGURE 2 | COVID-19 cases and fatalities were reported by age and gender (see text footnote 1).

This paper focuses on Computer-aided diagnosis (CAD), which has emerged as a key research topic in medical image processing and clinical diagnostics. Deep neural networks have recently achieved advancements in object identification, semantic segmentation, and picture classification in image recognition tasks. Robust object recognition from medical photos may relieve clinicians of a significant effort, provide solid quantitative assessments, and speed up the diagnosing process.

However, efficiently and successfully detecting sparsely dispersed items from large-scale data remains a difficult task.

- There is significant intra-class heterogeneity in the look of objects in medical photographs.
- Because the items are poorly dispersed, the approach must be efficient and resilient when applied to massive amounts of data.

The upcoming sections of this paper are organized as follows. Section Objective establishes the boundaries of the paper. Section discusses COVID-19 Diagnosis Using Chest Radiographic Images and Deep Learning. Section gives a detailed discussion of the noteworthy literature contributions to detecting COVID-19 infections. Section presents the Overhead for Detecting COVID-19 Using Traditional Methods and Improving the Detection Method Using Deep Learning Techniques. Section presents Recommendations. Section briefs Recommendations for Cost Minimization for Health Services. Section presents the Framework and Research Methodology used in this paper for shortlisting the dataset and manuscripts. Section gives the pointers for future research directions. Section concludes the paper.

OBJECTIVE

The paper's motive is to create a comprehensive analysis detection methodology based on Deep learning for COVID-19 diagnosis. The contributions of this paper are three-folds, are summarized in the following points,

- Study and comprehend the noteworthy Deep learning methods for COVID-19 diagnosis.
- To establish the financial Overhead for detecting COVID-19 using traditional methods and improving the detection method using deep learning techniques.
- To establish the Recommendation for Cost minimization for health services.

COVID-19 DIAGNOSIS USING CHEST RADIOGRAPHIC IMAGES AND DEEP LEARNING

Graphical Based Diagnosis Method for COVID-19

The apprehension methods used to distinguish the symptoms, like CT, identify discrete opacities contrasted to the healthy lung image and nucleic acid analysis, which implements real-time multiplex RT-PCR of well-known pathogens and generates negative and positive results (Serte and Demirel, 2021). The immediate preference for COVID- 19 symptomatic research, according to WHO, is the precedence of nuclear acid and protein tests, which effectively detect COVID-19 with the assistance of point-of-care detection. Serological examinations relating to protein are required in joining nucleic acid tests to advance surveillance exercises. This test serves to help with detection after healing and equips clinicians to trace infected and healed patients and to have a more reliable evaluation of an infection. Devices used to evaluate patients, like external periphery devices, can be implemented in areas such as city stations to reduce the load on medication laboratories (Irmak, 2020), where therapeutic care tests are priced optimally, conveniently, and easily handled.

Graphical-based symptomatic detecting techniques using deep learning in pandemics serve an essential purpose in screening for causes that comparatively render better outcomes than traditionally examined CXR and CT scans, amongst the principal radioscopy mechanisms in recognizing and diagnosing COVID-19 virus cases. The deep learning methodology is applied to investigating radiology images (Irmak, 2020). Appropriately identifying the COVID and non-COVID cases is a critical challenge in the non-COVID condition. For example, if people are grieving from bacterial pneumonitis dysfunctioning or other associations of pandemic infection are easily correlated with irregularity COVID-19. Similarly, lung-related diseases such as Pneumonia, which are strange, are infected with COVID but demonstrate similar symptoms, and all the diagnosis methodologies demonstrate the same kind of result.

Deep Learning Applications for COVID-19

The synthesis of in-depth training with medication and wellness is an innovative path to promote cutting-edge techniques. The paper encourages deep learning study to consider extensive applicability in multidimensions and effectively identify challenges such as COVID-19 or pandemic diagnosis. It is critical to accumulate expertise in crosswise utilization, such as data retrieval, image analysis, or protein structure forecast. It has potential and significant specific application with cutting-edge technology to intensify the supervised learning means for the appropriate diagnosis of Coronavirus. Deep learning has a big impact on the COVID-19 epidemic and opens up new research avenues. Deep learning has applications in simple semantic processing, machine perception, biology, and epidemiology. It broadens the scope of future repercussions, reveals incongruous data patterns, or interprets common sense. Precision diagnosis, protein structure prediction, and therapeutic repurposing are all possible.

Convolutional neural networks demonstrated their potential and established themselves as one of the most prominent deep learning algorithms and powerful techniques for detecting anomalies, irregularities, and diagnostics in chest radiography (Amyar et al., 2020). During a pandemic crisis, researchers focus on analyzing appropriate COVID-19 diagnoses by implementing a Convolutional Neural Network (CNN). Many studies have revealed that using deep learning algorithms could enhance the detection features of CT scan images and the consciousness, specificity, and efficiency of diagnosis (Zhang H. T. et al., 2020). Deep learning technology is a practical, valuable and suitable technique that can be deemed reliable for adequate diagnosis of the COVID-19 virus (Thepade and Jadhav, 2020). It demonstrates the potential to enhance image characteristics through artificial intelligence and distinguish the most inexpensive and most trustworthy imaging methods to anticipate dreadful viruses. Various researchers have recently carried out the application of deep learning for COVID-19. Some of the noteworthy contributions in the literature are from Asraf et al. (2020), Islam M.Z. et al. (2020), Muhammad et al. (2020), Islam et al. (2021), Rahman et al. (2021), Saha et al. (2021), Zhao et al. (2021), and Khasawneh et al. (2021).

Although the application of deep learning methods became game changers in identifying the COVID infections from the image data, researchers also come across a hard time efficiently implementing the solutions due to problems like Intra-Class Variation, Scale Variation, View-Point Variation, Occlusion, Illumination, and Background Clutter in the image data set.

TABLE 2 | Dataset used in different survey papers.

Dataset classes	Dataset used and its link
Multiclass-COVID19, community-acquired pneumonia, and normal	CT dataset (Ciotti et al., 2020; Jain et al., 2021) Xray dataset [Basu et al., 2020; I.s. of medical and i. r. (sirm), 2020]
Multiclass: COVID19, pneumonia, and normal	X-Ray dataset (Cohen and Morrison, 2020)
Both binary classes–COVID19 and Non-COVID19 and multiclass: COVID19, pneumonia and normal	Xray dataset (Shi et al., 2021, see text footnote 6)
Multiclass	X-Ray dataset (see text footnote 5)
Multiclass	X-Ray dataset (Cohen and Morrison, 2020)
Multiclass	X-Ray dataset (see text footnotes 7, 8)
Multiclass	Xray dataset (Basu et al., 2020; Wang et al., 2020)

DISCUSSION

Deep Learning is a subset of Machine Learning which can be used to train in supervised, semi-supervised, and unsupervised models. This is inspired by Artificial Neural Networks. Deep Learning can extract features from the data in a hierarchical fashion, i.e., at first low-level features are extracted, then mid-level features, and finally, high-level features are extracted. The main difference between machine learning and deep learning is that in machine learning, the dataset should be preprocessed thoroughly before being used to train the model. The data preprocessing step is not mandatory in deep learning since the models are robust to noise and missing data. Little to no data preprocessing is required.

Advancements in learning algorithms have given us various deep learning architectures during the last two decades. This helped us expand the number and type of problems that neural networks could solve. Deep learning is not a stand-alone approach, but it is a range of classification algorithms that one can apply to a range of problems.

The upcoming sections discuss the application of the Deep Neural Network in combating COVID-19. The data from the repositories given in **Table 2** is used to evaluate and compare the effectiveness of the related works used in this paper.

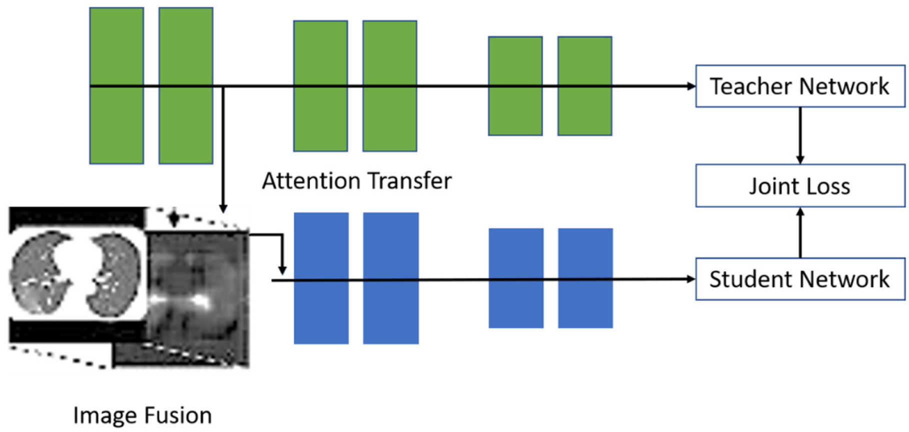

FIGURE 3 | The suggested architecture may be split into a teacher network and a student network (Shah et al., 2021).

The paper (Shah et al., 2021) proposed computer-aided diagnostic (CAD) technology encouraged by artificial intelligence technology to support radiology specialists in examining radiographic images quickly and increasing efficiency by employing the deep learning system and identifying a pattern of COVID-19 features in patients' chest radiographic images. Dataset link [Basu et al., 2020; Ciotti et al., 2020; I.s. of medical and i. r. (sirm), 2020; Jain et al., 2021]. The researchers have developed a knowledge distillation network topology based on explainable AI techniques; the framework of steps used is shown in **Figure 3**. There are two layers in the network: the teacher and the student network. The attention is generally transferred from the teacher to the student network. The focus of the teacher network is to extract the information that is globally available and emphasizes the critical infection areas to extract attention maps. The deformable attention modules will be employed, if the area of infection is large. This will further help in suppressing the noise in irrelevant areas.

Further, knowledge passed from the teacher's network to the student's network will be used in the image fusion step to combine the original input with the attention information. Normally, the teacher network focuses on the global level features, whereas the student network focuses on learning from the local discriminative features. After this, the concluding experiment is conducted using openly available datasets such as X-Ray/CT Scan images. These experiments established the explainability of the proposed architecture for diagnosing COVID-19.

The proposed methods (Shah et al., 2021) attention mechanism has demonstrated several advantages. Specifically, some state-of-the-art methods for employing attention mechanisms to improve the differentiation power of supervised learning models for X-Ray image processing tasks have been developed. The suggested architecture is shown in **Figure 3**.

The suggested approach[5] employs an X-Ray human chest dataset of un-infected individuals, pneumonia-affected and COVID-19 patients. For feature extraction, local dual patterns with mutable input attributes are considered. Many machine learning algorithms and ensembles classify the generated feature sets. Ten-fold cross-validation tests achieve experiment results. To compare performance, various accuracy comparison matrices are used. Results indicate that the Random Tree—Random Forests K-Nearest Neighbor (RTree-RForest-KNN) ensemble provides the best COVID-19 identification method proposed in the paper (see text footnote 5) based on two distinct stages, extraction and classification, where a local binary pattern is applied for extraction, which is further classified by a machine learning algorithm based on a 10-fold cross-validation testing methodology. The outcome illustrates that the R-tree, R-forest, and KNN frameworks achieve the best performance, whereas ensemble models outperform most individual classifiers. When comparing the Local binary patterns (LBP) input parameters, $R = 6$ ($P = 48$) and $R = 7$ ($P = 56$) provide the optimal result for 10-fold cross-validation in this COVID-19 identification method. Dataset link (Cohen and Morrison, 2020; Kim et al., 2022).

The researchers (Haritha et al., 2020a) propose a methodology to locate the region of infection using X-Ray images of the pulmonary area. The authors recommended two strategies because of the limited medical data and computation power available. First, developing a custom convolutional neural network model and training it by using a vast dataset of non-COVID-19 images of chest X-Ray of patients (ChexPert). Finally, tune that custom CNN model with COVID-19 X-Ray images; unfortunately, it did not provide optimal results. Thus, another proposed method used in the paper is transfer learning through a pre-trained CNN model based on Resnet50, VGG16, and Densenet121. The paper reached up to around 90 percent accuracy through the Densenet121 CNN methodology. The performance result is shown in **Figure 4**. Dataset link (Shi et al., 2021)[6]

[5]stanfordmlgroup: Xray dataset. Available online at: https://stanfordmlgroup.github.io/competitions/chexpert/

[6]Xray dataset. Available online at: http://www.sirm.org/category/senza~categoria/COVID-19/

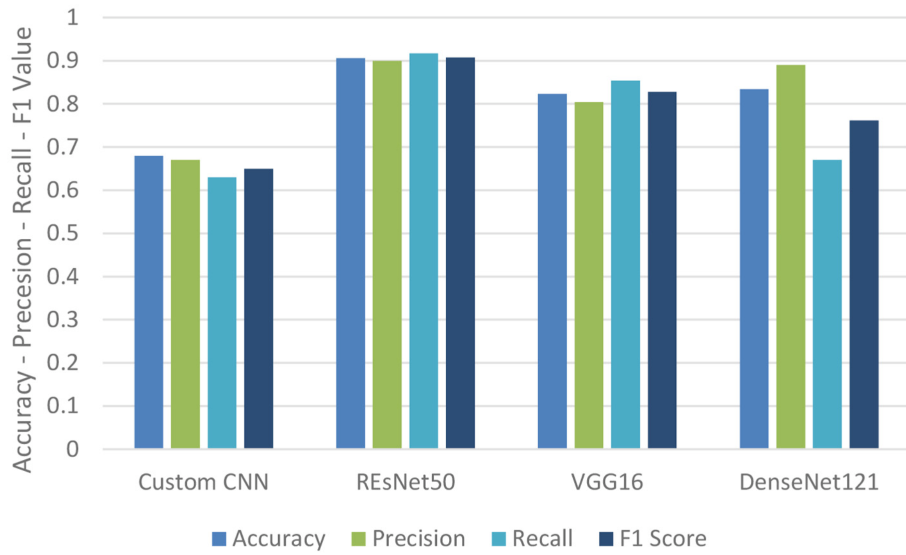

FIGURE 4 | Performance metrics table for binary classification (Haritha et al., 2020a).

TABLE 3 | DenseNet121 performance for multiclass (Haritha et al., 2020a).

Number of images	Prediction		
	Healthy (%)	**Pneumonia (%)**	**COVID19 (%)**
12	41.7	33.3	25
24	33.3	45.8	20.8
12	33.3	25	41.7

In the next step, the Multiclass scenario is considered by extending the problem by considering multiclass classification to identify if the patient is healthy, has Pneumonia not caused by COVID-19, or has COVID-19. The DenseNet architecture was employed for this prediction challenge, and the results metrics are shown in **Table 3**. The advantages of this paper are that to solve the problem of a lack of COVID-19-related data, the technique of transfer learning was employed, which provides improved accuracy.

The researchers (European Centre for Disease Prevention Control, 2020) in the paper concentrate on the detection of COVID-19 using transfer learning. This study uses a dataset of Chest X-Ray comprising 219 images of legitimate COVID-19 chest X-Ray images, as well as 1,341 and 1,345 images of ordinary and pneumonia cases, respectively. The database used for this experimentation is an open-source database available on the Kaggle site. All images are in PNG format and have a 1,024 × 1,024-pixel resolution. This data set has been subjected to many image preprocessing operations.

For this purpose, they used a distinct CNN model to achieve a good result. From the same perspective, the study (European Centre for Disease Prevention Control, 2020) examines pre-trained architectures of deep neural networks, including the ResNet50V2, VGG16, Xception, VGG19, MobileNetV2, and InceptionV3. Finally, they produced the statistical assessment metrics after drawing the confusion matrix. After examining the results, it was revealed that the Xception model produced an effective classification system compared to other models. The outcomes suggested that the Xception network performs significantly among all the models as it attains accuracy and sensitivity of up to 98 and 100%, respectively. All models, on average, attain a high level of precision of 97–98%.

Future research aims to create a model that integrates two transfer learning models to increase performance. This allows for a more accurate and timely diagnosis of COVID-19 patients.

To subdue the transmission of the pandemic in remote rural areas where people cannot afford expensive medical treatment, including the diagnostic expenses of the dreadful disease. The authors of the paper (Qjidaa et al., 2020a) proposed the AI system as a clinical decision support system (CDSS)for rapid and immediate diagnosis of COVID-19 from a chest X-Ray, which illustrates the dynamic potential (Qjidaa et al., 2020a). It is easier and less costly to access X-Ray imaging facilities for people living in rural locations. Five hundred and sixty-six radiology images were collected under three categories: COVID-19, Pneumonia, and Normal. The experimentation was carried out on 30% of test and validation data, and 70% of the original data was used for training. The proposed method is based on transfer learning, which uses seven distinct pre-trained models: VGG16, InceptionResNetV2, VGG19, Xception, DenceNet121, MobileNet, and InceptionV3. After analyzing the results of all models, combine the predicted classes of VGG16, VGG19, IceptionV3, Xception, DenseNet121, InceptionResNetV2, and MobileNet in a vector, and choose the class most frequently predicted by all models. It is possible to build a final classifier with a test accuracy of 99%, f1-score of 98%, precision of 98.60%, and sensitivity of 98.30% by employing this ensemble model methodology (Qjidaa et al., 2020a). This compiled technique demonstrates that the recommended methodology has a high potential to diagnose COVID-19. Dataset used (Cohen and Morrison, 2020).

The suggested model (Ghaderzadeh and Asadi, 2021), with 99.9% accuracy, the proposed model correctly classifies the binary classes of COVID-19 and normal images of patients' chest X-Ray images. CheXNet is a CNN architecture network trained to identify chest X-Ray abnormalities using the ChestXray14 dataset. In general, this model was enhanced to detect all 14 diseases in the dataset of chestXray14, and it employed a pre-trained Densenet121 model to identify COVID-19 and Normal binary class classifications. The dataset used to build this framework incorporates 1,824 evenly distributed thorax X-Ray images of COVID and non-COVID classes, i.e., COVID-19 is confirmed in 912 X-Rays and 912 non-COVID X-Rays. The dataset consists of two sets, training, and testing, with a ratio of 80:20.

The images are initially downscaled to 224 × 224 before being normalized and augmented with horizontal flipping, rotating, zooming, and rescaling, among other things. The initial model of CheXNet made use of the ChestX-Ray14 dataset, which is now the biggest accessible collection of chest X-Rays. CheXNet is a 121-layered deep Neural Network of the CNN type. This network generates a heat map to help with localization. This model was built in this paper (Ghaderzadeh and Asadi, 2021) using the dataset named ChestX-Ray14, which included radiographic images of X-Rays type from 14 distinct pathologies. Four professional radiology specialists classified the test set images in the dataset, and the model's output performance was compared. CheXNet was designed primarily to predict Pneumonia. Training the DenseNet121 model using 1,824 pictures showed outstanding results demonstrating that this model can predict with an accuracy of 99.9%. The improved performance, i.e., accuracy, of this model is attributable to the dataset used—since it represented the distinction—and another factor is that it considered the weights of pre-trained models that have already been trained using chest X-Ray images[7,8]

The researcher in the paper (Panwar et al., 2020a) recommends a therapeutic decision assistance method for the initial exposure of a pandemic utilizing chest radiology photographs and a deep learning methodology—the Dataset link (Basu et al., 2020; Wang et al., 2020).

The proposed methodology suggests a clinical decision support system that uses deep learning for the detection of COVID-19 based on chest X-Ray pictures. The architecture is divided into three stages to achieve this objective. The first stage entails input image preprocessing operations and then a data expansion process to increase the data size. The second step includes the extraction of features, followed by learning steps. Finally, a completely connected network with several classifiers is used in the third step to produce the classification and prediction process. This architecture has shown an internal validation area under the ROC Curve (AUC) of 0.97 and an external validation AUC of 0.95. The sensitivity of 0. 92, internal and external validation of 0 and 0.87, with specificity of 0.96 and 0.93, accuracy of 92.5 and 87.5%, negative predictions of 0.97 and 0.93, and 0.92 and F1 scores were 0.92 and 0.88. The outcome demonstrates that the design demands have the potential to distinguish and diagnose COVID-19 adequately to provide for specific, speedy, and practical clinical assistance practice in virus detection

The diagnosis equipment's capabilities are insufficient, creating ambiguity and inconsistencies among patients and physicians over the COVID-19 epidemic. Artificial intelligence exhibits the ability to fix the difficulty through its assistive and adequate usage in COVID exposure and forecast method. The study shows a model of COVID-19 foresight for thorax X-Rays using CoviNet. CoviNet, a deep learning network, was introduced in this paper (Knipe, 2020) to identify COVID-19 in chest X-Ray scans automatically. The foundations of the proposed design are a convolutional neural network, histogram equalization, and an adaptive median filter (Dodds et al., 2020). It is trained using a publicly available dataset. The model had a binary classification accuracy of 98.62% and a multiclass classification accuracy of 95.77%. This framework can aid in radiologists' work in COVID-19 diagnosis.

Many data preprocessing steps are performed, like labeling of dataset images (0 for normal images, 1 for COVID-19 patients' scan images, and 2 for other pulmonary illnesses), keeping images in grayscale, and using data augmentation approaches such as random rotation, vertical flip, and mirroring to solve the

The problem of data set class imbalances. CoviNet comprises an automated extraction feature and a classification component. CoviNet is based on a multi-layered CNN architecture (Knipe, 2020). After every convolution layer, the rectified Linear activation Unit (ReLU) was used as an activation function. By introducing max-pooling layers, computation complexity is minimized, and the feature maps generated. The resulting pooled output is then flattened and sent into the fully connected layer. The dropout is used to prevent overfitting concerns as a regularization strategy. Larger clinical datasets can be used in future work to properly test the model's performance and improve the segmentation step. The architecture of this model is shown in **Figure 5**.

The research (Cohen et al., 2020) aims to help radiology specialists interpret radiographs faster and more accurately by offering a deep learning system (Mask R-CNN) to analyze images and discover COVID-19 patterns in patients. In this study, a model based on X-Ray scans was developed to determine the severity of Pneumonia using a bounding box around the infected area.

Attempting to get deeper insights by making research more explainable. These bounding boxes might be used to train a Mask RCNN to classify imagery with Pneumonia and identify where Pneumonia is present within the image. This can assist doctors and radiologists in making more accurate patient diagnoses, saving time, and improving accuracy.

The initial images obtained from the dataset are in Digital Imaging and Communications in Medicine (DICOM) format. These are medical images that are saved in a specific

[7]http://md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com/bc9f750d-b663-48a7-844e-4e8246751706

[8]http://academictorrents.com/details/557481faacd824c83fbf57dcf7b6da9383b3235a

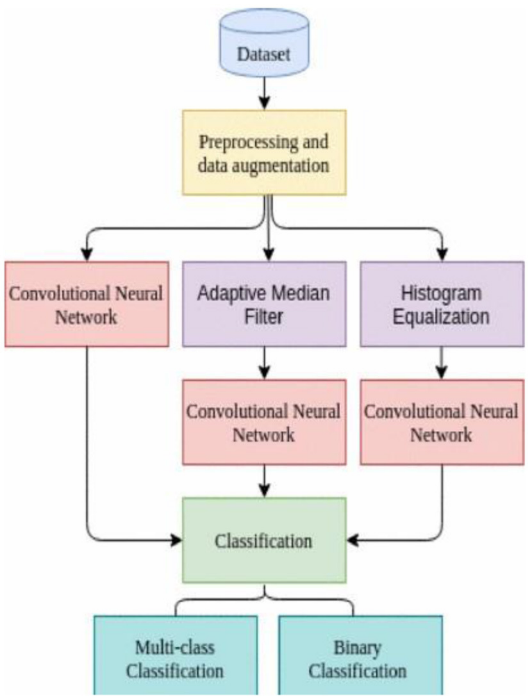

FIGURE 5 | Multi-layered convolutional neural network-based flow diagram of CoviNet (Knipe, 2020).

format known as DICOM Files (*.dcm). The primary goal of understanding the data structure, image file format, and label kinds is to detect the bounding boxes consisting of binary classification, i.e., presence (or) absence of Pneumonia. The dataset's classifications are split into Pneumonia (lung opacity), no pneumonia (lung opacity—not normal), and normal. Although the dataset is multiclass, a binary classification was employed to detect Pneumonia as positive (or) negative. If positive, what is the ROI for determining the severity of Pneumonia? (Cohen et al., 2020).

The Mask R-CNN X-Ray image can be more specific, reliable, and expertly diagnose the disease by recognizing the severity and the type recovered from the patient's image pattern through deep learning. The paper (Darapaneni et al., 2020) comprehensively analyzes a distinct set of data from Radiological Society of North America (RSNA) X-Ray images, one with Pneumonia and another with no pneumonia but irregular, and the third is the usual type. With the advancement of artificial intelligence, the CNN network recognizes individuals and serves their future potential. This will significantly affect experts focusing on critical cases to avoid the further expansion of the pandemic crisis. The outcome demonstrates that the data set's mean average precision (mAP) is achievable up to 0.90 for train data and 0.89 for test data.

Encouraged by artificial intelligence technology and to support radiology specialists in rendering images quicker and increasing efficiency by employing the deep learning system to examine the image and identify a pattern of COVID-19 in patients. The capability of measuring equipment is inappropriate, which engenders uncertainty and unreliability among patients and physicians regarding the COVID-19 pandemic. The 3-class (COVID-19, Normal, and Viral Pneumonia) detection research (Mohammed et al., 2020) was carried out in this study using SVM, employing.

Feature maps are derived from the ResNet-50 model, a CNN. Each image yielded a 1 × 1,000 attribute map. The research was conducted on 10 repetitions using a 5-fold cross-validation approach.

Residual Network, particularly ResNet 50 has been used to extract the features from the images. Further, the features extracted with the help of ResNet 50 have been fed to Support Vector Machines. Identifying COVID-19 with this method has reported the 96.35% in sensitivity (with the help of 5-fold cross-validation). The classification accuracy with SVM was reported near 99%. Depending on these promising results, it is anticipated that this approach will assist medical professionals while reducing the amount of incorrect identification.

Another work (Qjidaa et al., 2020b) describes CovStacknet's new distribution model based on the StackNet meta-modeling technique. Three datasets are used in the article. The very first dataset (DS1) contains 5,216 X-Ray pictures, 4,273 of which are pneumonia cases and 1,553 of which are normal cases. The second dataset (DS2) was made openly available for experimentation by Kaggle. The third dataset was made available to the public by the University of Montreal. In this work, Convolutional Neural Network named VGG 16 was employed to extract the required features from X-Ray. The feature set consists of 25,088 real array values for every picture, which the StackNet classifier will utilize as features.

The initial technique to feature engineering is a filter-based method in which each feature's variation is calculated, and features with variations smaller than a certain threshold (VarT) are discarded. When a character does not vary considerably within itself, it has minimal predictive value. The second feature selection strategy is feature rank with random forest. This method recommends more essential features to examine throughout the classification process. The Synthetic Minority Over-Sampling Technique (SMOTE) is the best way to handle unbalanced datasets. This strategy oversamples the instances in the minority class in the training dataset using the K closest neighbors' technique. Then, using the flattening layer VGG16, perform tensor flattening modifications to convert the feature matrix into a vector that can be fed into Stacknet (Qjidaa et al., 2020b).

They employed a variety of models based on several techniques to create a robust and efficient model, which was implemented using the Python Scikit-Learn package and pystacknet, an implementation of Stacknet. Initially, it consists of five estimators—one on the initial and final levels, the remaining three on the meta/intermediate level. The model classifies the input data into two categories: one with COVID-19 positive and another with COVID-19 negative. The proposed model was able to achieve an accuracy of 97%. This two-stage technique, which combines stages 1 and 3, results in exceptionally high classification scores compared to only one step, such as stage 2.

The research (Huang L. et al., 2020) demonstrates a new CNN framework for COVID-19 detection. The CNN architecture proposed consists of 12 weighted layers. These 12 layers are classified as two convolutional and fully connected layers. The SoftMax classifier receives an input from the fully connected layer, which generates a 2-dimensional feature vector. The output layer comprises two neurons since this model aims to categorize images into two categories: COVID-19 positive or negative. Dataset consists of a total of 625 pictures used in this study. This dataset is further divided into a subset of training, testing, and validation parts. The training part was used for building the model. Testing was used for testing the accuracy of the built model. The validation accuracy was used to find out the loss of the model and its accuracy. This model, which has a 99.20% accuracy, is used to evaluate whether a certain chest X-Ray image of a patient has COVID-19 or not. Experimental findings on clinical datasets validate the effectiveness of the proposed model.

The active and authentic pandemic diagnosis is probably implemented by a CT scan of the infected lung images. By implementing the deep learning methodology, convolutional neural network, the paper (see text footnote 1) is intended for CTnet-10. This model reported the COVID-19 detection with an accuracy of 82.1 percent. In addition, DenseNet-169, VGG-16, ResNet-50, InceptionV3, and VGG-19 were assessed. The VGG-19 outperformed all other deep learning models, with an accuracy of 94.52%. Finally, they concluded that clinicians might use CT scan pictures for automated COVID-19 diagnosis as a quick and effective strategy for COVID-19 screening (Huang L. et al., 2020).

The findings presented in the study (Udugama et al., 2020) demonstrated the use of transfer learning to detect COVID-19 using chest X-Ray images as input data. This method can classify the given input image data into infected and non-infected categories. This method specifically employed joint learning. The algorithms which perform well when joined are chosen, trained, and deployed as transfer learning. The model's training starts only when the input parameters of both the chosen models are feezed. The models which are pre-trained can be of various combinations. The combination of the model is decided and finalized based on the accuracy and loss value. The chosen models are made sure to change their weights dynamically to learn the patterns in the underlying data. The proposed method by the author has reported an accuracy of 96.1%. This method is proved to be effective in initial diagnostic and screening techniques for COVID-19.

The idea of a weakly supervised deep learning model was proposed by Lafraxo and El Ansari (2021). The proposed method by the authors collects the spatial, axial, and temporal information from CT scans. The Long Short-Term Memory (LSTM) is used for this feature extraction. The various resampling techniques are employed to handle the problem of class imbalance. The data is preprocessed with the help of stochastic and tone image mapping techniques. Finally, the suggested framework's performance is assessed using various module combinations. The proposed technique performed successfully in all evaluation measures and experimental scenarios regarding volume level prediction (Lafraxo and El Ansari, 2021). However, various experimental scenarios yielded varied results for slice-level prediction. In general, the integration of slice attention allows radiologists to concentrate solely on the most important parts of the entire CT volume. From a clinical standpoint, the suggested framework can help radiologists predict COVID-19. Furthermore, it lays the door for future studies aimed at detecting COVID-19 from limited and poorly labeled data.

The study proposed by Rabbah et al. (2020) uses an automated method for detecting COVID-19. It takes CT Scan images as input. As a preprocessing step, it uses pre-defined image processing algorithms. These image processing algorithms help to get the exact portion of the lung. The rest of the portion of the image which doesn't show significant information gets discarded. These preprocessing steps help in errors in classification. The algorithms proposed by the authors have significantly improved the accuracy in detecting COVID-19 from CT Scan images. This work mainly uses a feature pyramid network designed for special categories of classification tasks. This preprocessing will allow the model to investigate different picture resolutions without losing data from microscopic objects. Because COVID-19 infections arise in numerous sizes, many of which are tiny, this technique dramatically increases classification performance.

After completing these two steps, the system assesses the patient's state using a specified threshold. First, this system will be tested on Xception, ResNet50V2, and the proposed model. An accuracy of 98.49% has been achieved in classification concerning a single picture. The dataset consisting of 7,996 images was used for constructing, testing, and validating the model built as a part of this research.

Researchers (Dodds et al., 2020) proposed an automated distribution segmentation mechanism for assisting diagnose COVID-19 chest CT scans. This paper presented an original deep learning-based algorithm to identify COVID-19 infection. This work further extended to segment COVID-19 abnormalities with the help of CT scans. Three learning tasks are done concurrently with diverse datasets: segmentation, classification, and reconstruction. A common encoder with three jobs for disentangled feature representation employed a decoder, and for reconstruction and segmentation, it was implemented with the help of a multilayer perceptron. The evaluation of the proposed algorithm was done on the data set with 1,369 patient lung images, 449 of whom have COVID-19, 425 of whom are normal, 98 of who have lung cancer, and 397 of whom have other diseases (Dodds et al., 2020). The results show that this method works exceptionally well, along with a dice coefficient >0.88 regarding the segmentation phase and a ROC of 97% for classification.

The study conducted by Ni et al. (2020) employed a special classification technique maned binary image. This binary image classification technique is powerful and can efficiently distinguish/classify between COVID and non-COVID chest images. Furthermore, the study demonstrates that those who do not test positive for COVID-19 may have Pneumonia or other respiratory disorders. Many tests analyzed CXR and CT-Scan chest pictures to identify COVID-19 patients. The proposed methodology detects COVID-19 cases with 95.61% accuracy, significantly quicker than the traditional RT-PCR testing procedure.

The weights gained from training the proposed model during CT Scan image processing also offer a substantial response to CXR pictures. They also used a color visualization method in this. To detect COVID-19 instances effectively and with greater recall, it is recommended that the model be trained on radiological images of patients with Pneumonia symptoms. This will assist in the diagnosis of pneumonia patients as True Negative. As a result, COVID-19 symptoms are detected in an unbiased manner in real-time (Ni et al., 2020).

The work presented by Hernandez et al. (2020) has employed the automated deep learning algorithm on CT SCAN images. This method has the advantage of quantitatively characterizing the unusual patterns in the lung images. This study collected a rich database. This study evaluated the patient with COVID infection between January 1 and February 3. The results presented in this study are categorized into severe, moderate, and mild infections. The patients are asked to follow up during treatment. The pre- and post-COVID chest scans of the patients are collected and reanalyzed. It was revealed that the chest scan during pre, during, and after COVID has exhibited phenomenally different patterns.

In this study (Hernandez et al., 2020), researchers assessed the continuous changes in pneumonia seriousness in diverse clinical kinds of COVID-19 at reference line and addition scans using a measurable attribute repeatedly generated by a deep learning method using chest CT images. The primary research outcomes were that this deep learning could detect lung changes in COVID-19 infected patients with varying clinical severity. Patients with mild COVID-19 had a shorter time between the onset of symptoms and the first CT scan, indicating that they may have presented at an earlier stage of the illness. The decreased whole-lung and per-lobe QCT-PLO at baseline CT corroborated this. All severe and critical patients had a <90% pulse oxygen saturation. More than 50% of those polled felt dyspnea, which corresponds to a higher proportion of pulmonary opacification as evaluated by deep learning technology. The opacification rate increased considerably in the first follow-up, according to the findings. Nonetheless, there was no considerable rise in opacification % between the first and second follow-ups.

The method of detecting COVID at the image and scan level was proposed by Rahimzadeh et al. (2021). The algorithm's capability on the image level was evaluated first. This method has exhibited the highest classification accuracy level when the CT scan's central images are used as input data. Subsequently, the accuracy of the proposed method for detecting COVID-19 at the scan level is evaluated. It is noted that the percentage of accuracy is improved as the number/size of images in the dataset starts to grow. The proposed model exhibited an AUC of 0.9 and 0.67 for different deep learning architectures.

In this study (Yang et al., 2020), chest CT is crucial for COVID-19 diagnosis because it enables exact quantification and localization of abnormalities. They deployed deep learning-based software to assist in identifying, localizing, and quantifying COVID-19 Pneumonia. COVID-19 infection quantification and assessment by uAI: The uAI Intelligent Assistant Analysis System, a deep learning-based program, was developed by United Imaging Medical Technology Company Limited (Shanghai, China) specifically for COVID-19 evaluation. This artificial intelligence software uses a modified 3D convolution neural network and a combined V-Net with bottleneck components. According to the generalized linear mixed model, the dorsal region of the right lower lobe was the favored place for COVID-19 Pneumonia. A chest CT scan combined with analysis by the uAI Intelligent Assistant Analysis System may successfully detect Pneumonia in COVID-19 patients.

The quantitative determination performance of a deep learning model with radiological specialists in detecting abnormalities in chest CT images from COVID-19 patients is compared in the proposed study (Narin, 2020). A deep learning system for lesion recognition, segmentation, and localization was trained and validated in 14,435 patients with chest CT images and verified infection diagnosis. The quantitative identification performance of the proposed model was compared to the reading reports of three radiological residents and two experienced radiologists as the reference standard, with the accuracy, sensitivity, specificity, and F1 score assessed. The table of comparison between different COVID-19 detection methods and their strengths and weaknesses is shown in **Table 4**.

The study presented by Majeed and Hwang (2022) sheds light on the role of artificial intelligence (AI) and other latest technologies that were employed to fight COVID-19. This study gives an excellent comprehension of technologies assisted the early detection/diagnosis, trends analysis, intervention planning, healthcare burden forecasting, comorbidity analysis, and mitigation and control. On a broader note, this study has given the landscape of AI innovative applications in effectively combating with COVID-19 pandemic situation.

The medical fraternity and government agencies from various countries have invested huge amounts of revenue and time to invent a medication that can successfully suppress COVID-19. In this appalling time, efforts were made to use Artificial Intelligence and deep learning methodologies to combat the non-medical aspects such as tracking and forecasting outbreaks, detecting the non-compliance of infected patients, containing the outbreak, and identification of the hot zones which will help to contain the infection spread. Deep learning and AI played a pivotal role in detecting, classifying, and swiftly identifying the infection even in the medical image analysis of the dataset, such as CT, MRI, and X-Ray images. In healthcare, the role of AI and deep learning was quintessential and helped medical institutions and hospitals systematically provide faster diagnoses.

Due to the widespread essence of the Coronavirus, patients are being admitted to health care in batches. This had pushed the government and medical agencies to their edge to accommodate the higher number of admissions to the medical facility. Setting up an atmosphere where the patient can get quick treatment swiftly is daunting. Rapid diagnosis is quintessential and proven to be effective in containing the widespread COVID-19 virus. The mortality rate keeps rising worldwide, and it is evident when WHO (World Health Organization) decided to put nCoV as an epidemic disease on February 11, 2020, coiling the term COVID-19 which stands for Coronavirus Disease 2019.

TABLE 4 | Comparison of various models on COVID-19.

Title	Detection method used	Strengths	Scope for improvements
Performance evaluation of transfer learning technique for automatic detection of patients with COVID-19 on X-Ray Images	CNN based model having 6 layers VGG16, VGG19, Inception V3, Xception, ResNet-50V2, and MoileNet V2	Accuracy 98% and Sensitivity 100%	Accuracy and the sensitivity of the model decreases even if the slight increase in the noise level of the input data.
COVID-19 detection through X-Ray chest images	CNN model based on Resnet, VGG and Densenet	Accuracy 90% by Densenet	This model performance parameters dampen with the increasing size of the dataset.
Early detection of COVID19 by deep learning transfer Model for populations in isolated rural areas	CNN model based on Resnet, VGG, Xceptions, MobileNet, DenceNet121	Accuracy 99% Sensitivity 98.3%	Collection of the dataset from the rural COVID19 infected areas is a challenging task.
CoviNet: automated COVID-19 detection from X-rays using deep learning techniques	CoviNet embedded adaptive median filter, histogram equalization, and convolutional neural network	Accuracy 98.6% for the binary group and reveals 95.77% for the multiple class group.	CoviNet model is succumb to class imbalance problem if highly imbalanced data is used for training the classification model
COVID detection from chest X-Rays with deep learning: CheXNet	CheXNet	Accuracy 99.9%	More evaluation of the proposed method can be conducted by increasing the number of hidden layers in the proposed model.
A new classification model based on stacknet and deep learning for fast detection of COVID-19 through X rays images	CovStacknet based on StackNet meta-modeling	Accuracy 98%	
A novel deep convolutional neural network model for COVID-19 disease detection	Two convolutional layers followed by ReLU and max-pooling layers	Accuracy 99.20%	Evaluating the proposed method by employing a range of activation functions is necessary.
Machine learning-based approaches for detecting COVID-19 using clinical text data	K nearest neighbor classifier (k-NN)	Accuracy 96%	The proposed method takes clinical text data. It may contain noise. Noise can result in wrong diagnostic decisions.
COVIDiagnosis-Net: deep bayes SqueezeNet based diagnostic of the coronavirus disease 2019 (Ucar and Korkmaz, 2020)	COVID/Pneumonia/normal (3-class)	Binary: 98.08%, Multiclass: 87.02%	The model uses offline methods to do the preprocessing of the images.
COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images (Wang and Wong, 2020)	COVID/Pneumonia/normal (3-class)	Multiclass: 91.3%	Some of the hyperparameters which can be tuned are size of the network, number of layers, dropout rate, learning rate, kernel size etc. By varying these parameters after the initial learning, the performance can be improved over time, which is evident from the COVID-Net.
CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization (Mahmud et al., 2020)	COVID/Non-COVID (Binary) COVID/Non-COVID/Pneumonia (Multiclass)	Multiclass: 90.2%	The learning efficiency of the meta layer can be further improved by increasing the gradient of the activation function to obtain the better results.
Application of deep learning for fast detection of COVID-19 in X-rays using nCOVnet (Panwar et al., 2020b)	COVID/Non-COVID (Binary)	Binary: 97.08%, Multiclass: 87.33%	The response rate of the algorithm can be improved by training with a varied range of input images while at the training time.
Automated deep transfer learning-based approach for detection of COVID-19 infection in chest X-rays (Das et al., 2020)	COVID/Pneumonia/normal(3-class)	Binary: 99.02%	Combining multiple transfer learning approaches to the proposed method and evaluating the multiple combined transfer learning method needs to be studied.

Deep learning techniques also helped combat the socio-economic problems that took birth due to the COVID-19 pandemic. Many countries are using tools such as Dashboards, which are still helpful for the common people to get information about the precautions to be taken, the infection rate, fatality rate, etc. These dashboards are internally using various AI and deep learning models for processes such as data gathering or retrieval, assimilation of data, identification of the valuable insights from the gathered data from the various sources, and providing meaningful insights based on it in the dashboards.

OVERHEAD FOR DETECTING COVID-19 USING TRADITIONAL METHODS, AND IMPROVING THE DETECTION METHOD USING DEEP LEARNING TECHNIQUES

"Coronavirus disease 2019 (COVID-19) is a highly infectious disease caused by severe acute respiratory syndrome coronavirus 2" (Trehan, 2021).

"While the RT-PCR test is the gold standard for diagnosing COVID-19, it has limiting aspects with certain features that

TABLE 5 | Comparison of detection type and time in AED and INR.

Method	Type	COST (AED)	Cost (INR)	Time
CXR image	X-ray	220[9]	280[10]	∼5 min (Haritha et al., 2020b)
CT-scan image	PLAIN	2420 (see text footnote 9)	5720[11]	∼21.5 min (Huang Z. et al., 2020)
CT-scan image	With Contrast	2680 (see text footnote 9)	5720 (see text footnote 11)	∼21.5 min (Huang Z. et al., 2020)
RT-PCR	RT-PCR	150[12]	400[13]	∼4 h (Won et al., 2020)
The deep learning-based system	Graphical-design-based symptomatic techniques	220	100	∼1 min

make it difficult to diagnose the disease. RT-PCR is a very time-consuming, complex, costly, and manual process. One of the drawbacks of this method is the need for a laboratory kit, the provision of which is difficult or even impossible for many countries during crises and epidemics. Like all diagnostic and laboratory methods in healthcare systems, this method is not error-free and is biased. It requires an expert laboratory technician to sample the nasal and throat mucosa, which is a painful method, and this is why many people refuse to undergo nasal swap sampling. More importantly, many studies indicated the low sensitivity of the RT-PCR test; several studies have reported the sensitivity of this diagnostic method to be 30–60%, indicating a decrease in the accuracy of the diagnosis of COVID-19 in many cases. Some studies also pointed to its false-negative rate and contradictory results" [PubMed Central (PMC), 2021]. The drawbacks of manual testing include the sparse availability of testing kits and costly and inefficient blood tests; a blood test takes around 5–6 h to generate the result (Trehan, 2021).

"One of the main features of deep neural networks, in terms of their efficacy, is their employed architecture. Deep neural network architectures demonstrate an extraordinary ability to perform various functions for different data types [PubMed Central (PMC), 2021]." According to the findings, deep learning-based models have an extraordinary capacity to provide an accurate and efficient system for detecting and diagnosing COVID-19 cases. Their use in the processing of modalities would result in a significant increase in sensitivity and specificity value.

There are two important aspects of the examined method contributing to the detection and diagnosis of COVID-19 which are the test's duration and cost. **Table 5** shows that the duration of the COVID-19 test depends on the used method. In case RT-PCR was detected in ∼4 h; while the diagnosis time of CT scans is 21.5 min (see text footnote 1); and in the case of using X-ray chest images, the duration was <5 min (see text footnote 3). The evaluation period includes all processes, such as taking the swap or the image and sending it to the radiologist and relevant doctor. On the other hand, CT-scan and X-ray cost elements only count for imaging. The promoted method aims to support radiology specialists and doctors by automating the process by highlighting important medical features embedded in the medical images and for early identification of possible COVID infection status. This method will reduce the evaluation times and costs compared to manual processes.

RECOMMENDATIONS

The RT-PCR persisted as the most extensively accepted affirmative test for COVID-19 infection. However, this laboratory analysis has various loopholes. The RT-PCR technique on nasopharyngeal and thoracic swabs has low sensitivity and reliability concerns. Consequently, additional designs that couple radiological images, CT and X-Ray clinical indications, and laboratory inspections are practiced to acquire reliable outcomes. The chest CT scan and X-Ray images have been described as having high efficiency.

Artificial intelligence manifests immense potential in the contemporary cutting-edge world. The utilization of deep learning and machine learning techniques on CT scans and X-Ray images has promoted the more specific determination of Coronavirus. Based on chest radiographic images, deep learning and machine learning approaches have high precision in comparing COVID-19 with non-COVID-19 Pneumonia. This technique has expedited the computerized estimation and assessment of these images. To effectively analyze the inevitable role of artificial intelligence in today's medical world, where it has a dynamic capacity to rapidly interpret and diagnose the COVID-19 infection and aid in studying infection sequences.

The paper suggested that an AI-based methodology, like deep learning, is a machine learning procedure that prepares and trains radiographic data for the machine. This information can be bifurcated into corona-affected and non-COVID-19 related Pneumonia. The prognosis methodology for coronavirus detection and its outcomes with high certainty utilizes cutting-edge technology and manifest potential and is extensively practiced in therapeutic image processing and infection investigation studies using deep learning techniques.

Deep learning algorithms face difficulties because of the lack of transparency and representativeness of features in some radiographic images. It is challenging to discriminate between the many imaging features that have been used to evaluate the results. As no particular tactics can detect all lunglike

[9]Dubai Radiology Center. Available online at: https://www.drhc.ae/dubai-radiology-center

[10]Cost-of-X-Ray-chest-pa-view-in-India. Available online at: https://www.labsadvisor.com/cost-of-x-ray-chest-pa-view-in-india

[11]CT-scan-cost-in-India. Available online at: https://www.medicoverhospitals.in/articles/ct-scan-cost-in-india

[12]Fakeeh University Hospital—UAE. Available online at: https://fuh.care

[13]COVID-19 Package in Bangalore. Available online at: https://www.apollodiagnostics.in/bangalore/test/covid-19

dysfunctions based on just imaging exhibition on thorax CT scan or X-Ray, the relevance of a multidisciplinary strategy is suggested for overwhelming symptomatic effects. Other challenges faced during diagnosis include statutory insufficiency and the availability of enormous learning data. Massive, noisy data-limited recognition of the cross-crossing between computer science and medication, data secrecy, and protection concerns. However, the efficiency of the deep learning design and image-based modules that drive the variance among Coronavirus and other kinds of Pneumonia is being interpreted.

RECOMMENDATION FOR COST MINIMIZATION FOR HEALTH SERVICE

Pandemic has changed the working of the majority of organizations. All organizations are moving toward digitizing their day-to-day operations. The insurance industry is not an exception. More and more financial service providers are increasingly moving toward digitization and utilizing AI-based tools. With the emerging wave of Machine Learning, Deep Learning, and Artificial Neural Networks—AI has made its legitimacy and its initial steps in solving the majority of the challenges in financial tech companies. Financial organizations are forced to shift from detecting and repairing work to predicting and preventing mode in this makeshift. This mode of operation needs to be coped up with everyone directly and indirectly associated with the organization.

The ongoing deep penetration of AI technologies is forcing insurance organizations to change according to the wave and cope with the change by adopting it.

State of the Insurance by 2030

There will be a tremendous change in the operation of the insurance industry in another decade. The currently followed processes in the organizations will be outdated. Advanced technologies will soon replace the legacy systems of operation. This will bring a dramatic change in the insurance value chain.

Distribution

Insurance distribution will happen much more swiftly without more involvement and contact between the insurer and customer (Kaesler et al., 2020). AI-based algorithms will gather the insurance risk-related policies and the necessary information to make informed decisions. Some of the leading insurance agencies are already testing the distribution change trend.

The insurance agencies will start using an immutable transactional distributed database for record-keeping—the technology called Blockchain. The information present in the blockchain network is known to everyone, but no one can modify it without all participating nodes' consensus. Insurance information that is currently centralized will become public and more transparency will be induced.

Claims

The primary efficiency of any insurance organization is the fastness and accuracy with which the claim is being processed. The claim processing will remain the paramount factor of importance by 2030. Highly sophisticated algorithms will be employed to claim routing, efficiency, and accuracy in claim processing. Additionally, automatic customer applications will be deployed at the customer's disposal, which can be accessed through mobile, web, or wearable smart devices. Claim triggers and repair services will be automatically triggered upon loss (Fong et al., 2020).

TABLE 6 | Survey framework.

Objectives	1. Literature collection on the recent works done for COVID-19 detection 2. Literature survey on the dataset discovery and aggregation 31. Explore the CNN architectures, machine learning algorithms for the techniques for COVID-19 detection and classification 4. Explore the architectural designs and patterns for basing the proposed work
Survey methods	Systematic exploration of articles, white papers, journals, and medical databases/journals
Databases explored	IEEE-Xplore, Elsevier Journals, Radiopedia.org, Springer databases, acs.org, GitHub databases
Datasets accumulated	CT Dataset (Ciotti et al., 2020; Jain et al., 2021) Xray Dataset [Basu et al., 2020; I.s. of medical and i. r. (sirm), 2020] X-Ray Dataset (Cohen et al., 2020) Xray Dataset (Shi et al., 2021, see text footnote 6) X-Ray Dataset (see text footnote 6) X-Ray Dataset (Cohen and Morrison, 2020) X-Ray Dataset (see text footnotes 7, 8) Xray Dataset (Basu et al., 2020; Wang et al., 2020, 2017; Zhang J. et al., 2020)
Keywords	Deep learning for COVID-19, COVID-19 classification and detection, convolutional neural networks, transfer learning, ensemble learning
Inclusion criteria	COVID-19 classification using CNN's
Exclusion criteria	Machine learning for COVID-19 and its relevant works
#Papers collected	127
#Papers shortlisted	70
Outcomes achieved	1. Architectures summary presented in **Table 4** 2. Datasets examined under the survey is presented in **Table 2** 3. Analysis of each architecture is presented under discussion (Section Discussion)

FRAMEWORK AND RESEARCH METHODOLOGY

The following **Table 6** summarizes the survey framework used for the study.

FUTURE RESEARCH PROSPECTS

In a short span, COVID-19 has posed several challenges and opportunities. Solving these challenges will yield more significant benefits for the research fraternity at large. This section briefs

FIGURE 6 | Research prospects.

some of the pressing challenges that surfaced due to the pandemic situation. Any researchers willing to take up COVID-19-related research topic can further explore the pointers given in this section. Each one of the pointers given in the rest of the sections can be explored in-depth, and suitable solutions can be proposed.

Data Science related areas could actively contribute to finding out the solutions for threats developed due to infection, severity, and outcome risk. Infection risk is related to groups of people and the most susceptible individuals in that group. Severity risk is related to a specific group of individuals developing severe disease symptoms and complications. Outcome risk is related to the treatments and their outcome. The summary of the future research prospect is illustrated in **Figure 6**.

There are various realms from which the challenges related to COVID-19 look challenging, if effectively solved, it could serve medical eternity to a larger extent.

The aspects to be considered for enhancement range from time complexity, space complexity, data quality, recording, record keeping, transfer learning, and the aspect of transition networks. All these aspects need to be critically brought under the scrutiny of future research exploration.

There are some other aspects too from which the problems need to be solved. There needs to be methods and techniques that facilitate faster development and discovery of drugs. It is more important to find out if the already available drug can cure the new disease. For this to happen, one should know the ontology of the disease and the characteristics of the new disease. Other dimensions involve understanding the path of the virus, in other words, or to trace the virus entry point. Some other important aspects are Screening patients using face scans. Building biomedical knowledge graphs, predicting drug-target interactions, Predicting the spread of infectious disease using social networks, understanding viruses through proteins, and predicting viral-host protein-protein interactions.

CONCLUSION

The application of deep learning in COVID-19 radiologic image processing reduces false positives and negatives and offers a unique opportunity to provide fast, cheap, and safe diagnostic services to patients. The convolutional neural networks have demonstrated their potential and convinced themselves to be among the most prominent deep learning algorithms and powerful techniques in identifying anomalies, irregularities, and diagnostics in chest radiography. During a pandemic crisis, researchers focus on analyzing appropriate COVID-19 diagnoses by implementing CNN technology. The research revealed that using deep learning algorithms could enhance the detection features of X-Ray and CT scan images and the consciousness, accuracy, specificity, and efficiency of the diagnosis.

This paper summarized AI-based deep learning methods and performance challenges to demonstrate rapid virus diagnosis and detection potential. Furthermore, the study allows a comprehensive summary of the existing state-of-the-art techniques and reinforcements for deep learning, CT scan, X-Ray, and machine learning practices exhibited by the more comprehensive wellbeing alliance, expressing how deep learning and machine learning regarding information will heighten the situation of this pandemic.

Additionally, this paper further discusses the cost-effectiveness of the surveyed methods for detecting COVID-19, in contrast with the other methods. Several finance-related aspects of COVID-19 detection and the effectiveness of different methods used for COVID-19 detection have been discussed. This study presents an overview of COVID-19 detection using deep learning methods and their cost-effectiveness and financial implications.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Cross Country Determinants of Investors' Sentiments Prediction in Emerging Markets Using ANN

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The paper models investor sentiments (IS) to attract investments for Health Sector and Growth in emerging markets, *viz*., India, Mainland China, and the UAE, by asking questions such as: What specific healthcare sector opportunities are available in the three markets? Are the USA-IS key IS predictors in the three economies? How important are macroeconomic and sociocultural factors in predicting IS in these markets? How important are economic crises and pandemic events in predicting IS in these markets? Is there contemporaneous relation in predicting IS across the three countries in terms of USA-IS, and, if yes, is the magnitude of the impact of USA-IS uniform across the three countries' IS? The artificial neural network (ANN) model is applied to weekly time-series data from January 2003 to December 2020 to capture behavioral elements in the investors' decision-making in these emerging economies. The empirical findings confirmed the superiority of the ANN framework over the traditional logistic model in capturing the cognitive behavior of investors. Health predictor—current health expenditure as a percentage of GDP, USA IS predictor—spread, and Macro-factor GDP—annual growth % are the common predictors across the 3 economies that positively impacted the emerging markets' IS behavior. USA (S&P 500) return is the only common predictor across the three economies that negatively impacted the emerging markets' IS behavior. However, the magnitude of both positive and negative impacts varies across the countries, signifying unique, diverse socioeconomic, cultural, and market features in each of the 3 economies. The results have four key implications: Firstly, US market sentiments are an essential factor influencing stock markets in these countries. Secondly, there is a need for developing a robust sentiment proxy on similar lines to the USA in the three countries. Thirdly, investment opportunities in the healthcare sector in these economies have been identified for potential investments by the investors. Fourthly, this study is the first study to investigate investors' sentiments in these three fast-emerging economies to attract investments in the Health Sector and Growth in the backdrop of UN's 2030 SDG 3 and SDG 8 targets to be achieved by these economies.

Keywords: investor sentiments, emerging markets, market index return, ANN, SDG 3, SDG 8, health financial management

BACKGROUND

Many global pronouncements and Country/Territory commitments, such as the Universal Health Coverage (UHC) resolution adopted by the United Nations General Assembly, have placed UHC at the forefront of health policies and plans. While some nations have already achieved universal health coverage (UHC), the majority are still working toward it. Progress is inconsistent among countries, and there are gaps in knowledge and funding about how to successfully go from policy to achievement in the face of limited resources. A glance at the summary of the healthcare sector and economic indicators in Mainland China, India, and the UAE in **Table 1** shows that population-wise, Mainland China is the first thickly populated economy (1414.049 million) globally followed by India (1324.517 million). In comparison, the UAE is a very small economy with a population of 9.771 million.

Current health expenditure (CHE) as a percentage of GDP is highest in Mainland China (5.3503%), followed by the UAE (4.27%) and India (3.014%). On the other hand, Government financing arrangement (GFA) as a share of CHE is highest in the UAE (50.86%), followed by India (27.58%) and Mainland China (16.86%). This implies that the UAE has significantly financed the CHE of its population from its internal resources, while India and Mainland China have partially covered the CHE from their internal resources, leaving the rest of the CHE covered by the private and household sector resources. Despite this, Mainland China's UHC index as of 2019 is 82, followed by the UAE with 78, and India lags with an index of 61. These indicators highlight that Mainland China has attracted the highest volume of $187,169.82 million as net investment inflow through domestic and foreign direct investment (FDI), compared to $50,610.65 million by India and $13,787.47 million by the UAE. India runs a fiscal deficit of US$ 30,918 million, while Mainland China and the UAE have surpluses due to robust manufacturing and export fundamentals and oil revenue, respectively.

De Long et al. (1990a,b), Dimic et al. (2018), Kapar et al. (2020) study shows that countries well-integrated internationally have a more efficient capital allocation, risk-sharing opportunities, better governance, higher investment, and growth through vibrant quality financial markets. Financial market quality is a function of market efficiency and integrity that equilibrates between these two elements and is critical to enhancing market prosperity and competitiveness (Kapar et al., 2020).

Section Healthcare Trends Post COVID-19 of this study provides an overview of the healthcare sector situation in the three economies, which identifies the opportunities in the healthcare sector for domestic investors and attract foreign direct investment (FDI). Section Literature Review And Conceptual Framework reviews the relevant IS literature to develop the IS conceptual framework. Section Methodology and Data discusses the methodology and empirical data. Section Model Results discusses the model results and presents the main findings. Section Conclusion and Limitations concludes with limitations and practical implications.

HEALTHCARE TRENDS POST COVID-19[1]

Following are the challenges and prospects that are likely to be hallmarks of the post-pandemic world, representing the "new normal" for the industry:

- Increased consolidation [*via* merger and acquisition (M&A) activity] in the global and regional healthcare industries, as smaller private healthcare firms increasingly face liquidity problems due to the pandemic's revenue decline.
- Resumption of elective surgery on a phased basis (that had been postponed during the pandemic).
- With a stronger government focus on healthcare spending, policies and decision-making will most likely be more efficient and coordinated.
- International cooperation between governments at all levels. For example, the World Health Organization and other international and state health organizations will watch the potential for viruses to arise.
- New care models will emerge, such as more digitalization, emphasizing remote monitoring and consultation. In addition, telehealth or communication technologies to obtain healthcare from a distance are expected to be included in public-private partnerships (PPP) models and government healthcare systems.

Healthcare Sector and Investment Opportunities in India[2]

As investments play a crucial role in economic development, regulators motivate investors to invest in their countries/territories by maintaining market quality to attract FDI. The growth of the Indian healthcare sector is being fuelled by several factors, such as an aging population, a growing middle class, a rise in the prevalence of lifestyle diseases, an increased emphasis on PPPs, and accelerated adoption of digital technologies (including telemedicine), among others. The Indian Government has implemented long-term structural changes to improve the healthcare industry and set

[1]KPMG (2020). Available online at: https://assets.kpmg/content/dam/kpmg/ae/pdf-2020/09/uae-healthcare-perspectives.pdf.

[2]https://www.investindia.gov.in/sector/healthcare

TABLE 1 | A summary of healthcare sector and economic indicators in Mainland China, India, and the UAE [as of 2019 (source: www.who.org)].

Indicators	Mainland China	India	UAE
Population (in Millions)	1414.049	1324.517	9.771
Current Health Expenditure (CHE) as % of GDP	5.3503	3.014	4.27
Government Financing Arrangements (GFA) as % of CHE	16.86	27.58	50.86
UHC index	82	61	78
GDP per capital in US$	10,002	2,115	43,103
Foreign direct investment, net inflows (BoP, current US$ Million)	187169.82	50610.65	13787.47
Balance of payments, supplementary items. Total Current + Capital Account, US$ Million	30,163	−30,918	12,707

policies to encourage FDI. Many health-related policies are included in the Aatmanirbhar Bharat Abhiyaan packages,[3] such as production-linked incentive (PLI) schemes to stimulate domestic pharmaceutical and medical device production. Additionally, India is attempting to become a center for spiritual and wellness tourism, as the country/territory offers Ayurveda and Yoga resources.

India has benefited from the COVID-19 pandemic in several ways. Due to the situation, numerous Indian start-ups have stepped up to the plate and hastened the development of low-cost, scalable, and rapid healthcare solutions. This is encouraging. India's healthcare sector is open to investment because of these characteristics. An interesting investment opportunity exists in the hospital sector, where private firms expand into Tier 2 and Tier 3 cities outside urban areas. With the latest PLI schemes, India can also increase domestic pharmaceutical manufactures and provide investment opportunities in contract manufacturing and research, over-the-counter medications, and vaccines. India is also a great place for medical device manufacturers with numerous diagnostic and pathology centers and miniaturized diagnostics. The healthcare sector was the fifth-largest employer in 2015, according to research from KPMG and FICCI. Between 2017 and 2022, the health sector is expected to create over 2.7 million new employment, or over 500,000 new jobs annually, according to the National Skills Development Commission (NSDC).[4]

The employment patterns in the healthcare industry have extra multiplier effects and distributional advantages aside from the direct influence on jobs and economic growth. Since it employs so many women, the healthcare industry has the potential to increase the share of Indian women in the labor force. Women's work opportunities in the healthcare industry are notably highlighted in the WHO High-Level Commission on Health Employment and Economic Growth's final report from 2016. In addition, the health sector generates more jobs and economic activity than the non-health sector due to these jobs and economic activity. WHO estimates that, for every dollar invested in healthcare, there is an additional USD 0.77 in economic growth due to that investment's indirect and induced impacts. As a result, more people will be able to afford to pay for their health insurance premiums due to increased manufacturing and service outputs and the purchase of new equipment and education and training.[5]

Additional jobs will be created in India due to the expansion of insurance and the digitization of the healthcare sector. As part of the National Digital Health Mission (NDHM), for example, staff will be needed to digitize family records at all levels of the health care system. HIT (Health Information Technology), Health Informatics, and Medical Informatics (also referred to Clinical Informatics) are among the fields that necessitate human resources. As the last point, the advent of Ayushman Bharat in 2018 has opened up new avenues for employment development. Health and Wellness Centers (HWC), with a population of 150,000 or more, will be run by a multidisciplinary team that includes a midlevel health provider (MHP), additional nursing midwives (ANMs), and additional social health activists (ASHAs), and a male health worker.[6] To run the HWCs, around 150,000 MHPs will need to be in charge.

With private equity (PE) funding, there has been a significant increase in multi-specialty and single-specialty hospitals. When India opened the hospital industry to 100% FDI in 2000, there was a rush of investments, mainly from outside funds (see footnote 6). India's healthcare providers have received investments from more than 110 private equity (PE) and venture capital (VC) firms. In 2019, the value of hospital mergers and acquisitions reached a record of $1.09 billion.[7]

Healthcare Sector and Investment Opportunities in Mainland China[8]

Both Mainland China's strengths and shortcomings have been exposed by the coronavirus (COVID-19) pandemic. Providing

[3] https://aatmanirbharbharat.mygov.in/

[4] Human Resource and Skill Requirements in the Healthcare Sector. NSDC, Ministry of Skill Development & Entrepreneurship, Government of India. Retrieved 29th March 2022 from https://skillsip.nsdcindia.org/knowledge-products/human-resource-and-skill-requirements-health-sector.

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Financing and Funding Indian Healthcare: Navigating the Turbulent Tide. PwC India. Retrieved 29th March 2022 from https://www.pwc.in/assets/pdfs/publications/2018/financing-and-funding-indian-healthcare-navigating-the-turbulent-tide.pdf.

[7] https://assets.kpmg/content/dam/kpmg/ae/pdf-2020/09/uae-healthcare-perspectives.pdf

[8] https://www.dezshira.com/industries/healthcare; https://www.china-briefing.com/news/investment-opportunities-chinas-healthcare-sector-after covid-19/

emergency hospital beds and conducting comprehensive testing allowed the Chinese Government to significantly expand the Country/Territory's short-term healthcare capabilities. However, there were significant differences in quality of care among hospitals across areas due to this outbreak. There are numerous investment prospects in Mainland China's healthcare market, which had been predicted to be worth US$2.3 trillion by 2030, as a result of COVID-19 and its lessons learned.

There Will Always Be a Push for Increased Healthcare Spending

Increased investment in Mainland China's healthcare system may result from the coronavirus pandemic. Mainland China's rapidly aging population and economic growth have already put the country/territory on a trajectory for significant increases in healthcare spending. Although Mainland China's population is aging at an unprecedented rate, the percentage of persons 65 and older is expected to rise from 10 to 20% by 2037. According to the United Nations, by 2050, 27.5% of Mainland China's population will be 65 years old or older, up from 9.5% in 2015. The coronavirus may stimulate structural upgrades and reforms to Mainland China's healthcare system, even if more healthcare spending was already predicted in the long run. Chinese authorities made investments in areas where the healthcare system's flaws were exposed after the 2003 SARS pandemic. This included increasing transparency, enhancing infectious disease surveillance, investing in public education, and establishing disease reporting systems and control centers. Authorities will undoubtedly launch similar measures in the months and years following the containment of the coronavirus.

Hospitals' Ability to Perform at a Consistent Level

Although there is a wide range of hospital capabilities between areas, there is also a wide range of hospital capabilities even inside a single city. Patients in Mainland China are more likely to receive care from large and well-equipped hospitals. Only 8% of hospitals are responsible for more than half of all patients. According to Bain & Company, there were just 10 community hospitals in Wuhan, the outbreak's epicenter, equipped to treat patients with coronavirus symptoms.

Infrastructure for Healthcare

According to the city's health authority, 94% of Wuhan's hospital beds were occupied. The widespread usage of mobile apps in Mainland China's response to the coronavirus has been a significant aspect. In contrast to the SARS pandemic, where individuals relied on official channels to obtain information and received conflicting messages, the coronavirus outbreak has allowed citizens to stay informed in real time.

Making Social Media Apps More Useful

WeChat and Weibo, two of the most popular social media apps in Mainland China, have emerged as sources of public health information and a way for users to provide comments. A Chinese internet giant, Baidu, has also enhanced its map app to show locations where infections are more likely to occur. When a crisis occurs, stakeholders of all kinds should use new media to communicate and share medical information, not only the traditional ones.

There Are a Lot of Healthcare Apps Out There

In reaction to the coronavirus, healthcare apps, including Ping-An Good Doctor, Ding Xiang Yuan, and Chunyu Doctor, saw a substantial increase in user numbers. As of January 2020, Ping-An Good Doctor reported a rise of 900 percent in the number of new users. Patients with questions about their health or concerns about their symptoms could turn to apps like Ping-An Good Doctor for help. One can also book doctor's appointments, buy drugs and healthcare supplies, and get discounts on the app. In a move that has sparked outrage, the city of Hangzhou has developed a mobile health app that Alipay and WeChat host. Users' health stats are colored green, yellow, or red to indicate whether they should be quarantined and may also be shared with government officials. Although digital health services are still in their infancy, they hold a lot of promise as a source of future investment and expansion in the healthcare industry. Support for telemedicine and digital healthcare will likely be a priority for government planners in the forthcoming years as 5G and the Internet of Things (IoT) become more widely adopted.

Technology

Hard technologies and digital tools are being used creatively by the Chinese Government and commercial companies to tackle the coronavirus. Drones spray disinfectants, transport medical samples, perform tests, and distribute consumer items to businesses and municipal governments. A micromulticopter in Shenzhen deployed its drones to transport medical samples and perform thermal imaging tests. The e-commerce company JD used drones to carry supplies to the island village of Anxin after coronavirus containment efforts disrupted ferry services. The employment of robots to aid medical personnel is also being tested in Chinese hospitals. At Wuhan's Hongshan Sports Center, a so-called "Smart Field Hospital," patients' temperatures, vital signs, heart rates, and other indicators are being monitored by robots and IoT technology. Food and medicine are delivered by robots in hospitals and hotels, eliminating human contact and the spread of infectious diseases.

Healthcare Sector and Investment Opportunities in the UAE[9]

Hospitals and clinics have mushroomed across the United Arab Emirates, a testament to the country/territory's booming healthcare sector. It is still one of the fastest-growing industries in the UAE. COVID-19 was a massive stress test for the sector. Everything from the strategic operations of governmental agencies to the provision of high-quality medical treatment and support was affected significantly by the pandemic. Local regulatory authorities' responses were prompt and well-thought-out. KPMG (see footnote 7) has identified the following six dynamics central to understanding the intricacies—and the future—of the UAE's healthcare sector.

[9] http://www.alpencapital.com/downloads/reports/2018/GCCHealthcare-Industry-Report-March-2018.pdf

Public vs. Private Investment

Private investors are projected to cover most of the cost of future healthcare expenditures. By pushing the implementation of PPP models, there is a push to increase private sector spending. Increased demand for specialized healthcare sector skills (e.g., cardiology) that are currently lacking in the UAE is a major factor in promoting private investments. As of 2018, private healthcare spending is expected to have grown at a compound annual growth rate (CAGR) of 9.5 percent, while the government contribution is expected to have grown at an annual rate of 4.4 percent. Increasing demand for treatment and hospital beds among an aging population in the United Arab Emirates is a significant factor in the country/territory's growth.[10] A more integrated health care system is likely to be encouraged by the privatization of hospitals and mandated medical insurance, especially in Dubai and Abu Dhabi.[11]

The Increasing Importance of Primary Care

It is critical to have an initial diagnosis right at the beginning of the patient journey in primary care before a simple illness pattern becomes complex and/or life-threatening. Healthcare systems around the globe rely heavily on primary care. As a result, countries are progressively investing in the infrastructure they need. The primary care system in the UAE is considered to be in its infancy by many industry observers. The rise in lifestyle diseases (such as diabetes) in recent years has presented a chance to considerably improve the general wellbeing of the population through upgraded, relevant primary care options like daycare facilities.

The Effect of Technology and Digital Health

It is becoming more and more common for health regulators in the UAE to contemplate the implementation of cutting-edge technologies to improve the healthcare system. As a result of increased AI use, the country/territory's GDP is expected to grow by USD 182 billion by 2035, which will help it achieve its goal of being a top healthcare technology hub across the world[12] Because of the pandemic's uncertain impact, all predictions must be considered cautiously.

Healthcare Workforce Considerations

Due to the global lack of healthcare workers, people may need to be retrained or re-educated. Hospitals and other health care facilities around the world are running low on resources. As a result, 18 million health personnel are predicted to be in short supply by 2030, according to a report by the WHO (Shefrin, 2001; Barber et al., 2009; Britnell, 2019; Kumari, 2019). There has been a significant increase of medical students in the UAE because of the country/territory's abundance of medical schools.

[10] http://www.alpencapital.com/downloads/reports/2018/GCCHealthcare-Industry-Report-March-2018.pdf

[11] https://www.pressreader.com/uae/forbes-middleeast/20191223/281805695836430

[12] https://internationalfinance.com/public-private-collaborationkey-to-uaes-smart-healthcare-goals/

Medical and Wellness Tourism

In 2019, the worldwide health tourism business was expected to bring in about USD 32.5 billion, representing a CAGR of 17.9 percent between 2013 and 2019. By 2027, the market is estimated to reach USD 207.9 billion, with a CAGR of 21.1 percent. Middle-class communities worldwide, particularly in Asia, are becoming more and more able to travel overseas for medical treatment. The most recent Medical Tourism Index Ranking has placed Dubai at No. 6 and Abu Dhabi at No. 8 among the world's top medical tourism destinations.[13] The more comprehensive, well-established travel and tourism ecosystem, including numerous attractions, hotels, entertainment, and world-class, internationally extensive aviation services and strong transport logistics, further supports the UAE's potential as a medical tourism destination.

Niche Areas of Underserved Healthcare

UAE has seen a tremendous increase in healthcare infrastructure over the past 5 to 10 years, yet several specialties remain neglected. For example, if healthcare providers lack maternity, pediatric, elderly, and fertility services; one-stop health care centers; and diabetes treatment centers, then the UAE's healthcare authorities face one of the greatest problems.

The Rationale for the Choice of the Three Economies

The choice of Mainland China economy through the Shanghai Stock Exchange (SSE), India's economy through the Mumbai Stock Exchange (BSE), and the UAE economy through Dubai Financial Market (DFM) and Abu Dhabi Securities Exchange (ADSE) is logically due to the global vibrancy and fast developing nature of these emerging stock markets in terms of their capitalization. Both Mainland China and India have strong trade relations with the UAE. Furthermore, their associated economies are also highly socio-culturally diverse economies globally. UNDP, in terms of the Human Development Index (HDI) in 2019-20, ranked UAE 31 (very high HDI), Mainland China 85 (High HDI), and India 121 (medium HDI). These unique features make the research questions worthy of investigation in terms of their importance/impact on IS to attract investments in these economies' healthcare sectors.

LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

This section reviews literature related to the three financial markets, followed by an extant literature review to show the low degree of IS research done in these markets.

Indian Financial Market

Foreign institutional investors (FIIs) dominate capital market activity with almost 70% share. The prominence of a few players, excess volatility, and lack of clarity on regulatory provisions have affected the functioning of Indian financial markets (Shiller, 1981; Lee et al., 1991; Shleifer and Vishny, 1997; Das and Pattanayak,

[13] https://www.medicaltourism.com/destinations/dubai

2013). There are very few studies analyzing investor behavior. The challenge is the lack of a well-defined proxy to measure IS in the Indian context. It is difficult to tell whether the markets are influenced by optimism or anxiety because the sentiments are not readily observable. Kumari and Mahakud (2015) employ VAR-GARCH models to investigate the effect of IS on the equity market volatility. They find a significant effect of IS on the stock market volatility. Jana (2016) finds a weak relationship between IS and returns in the Indian equity market. Recently, Chakraborty and Subramaniam (2020) have used a market-based measure, Market Mood Index (MMI), and a survey-based measure Consumer Sentiment Index (CSI) as proxies for IS. Their results show that IS plays a vital role in predicting stock market return.

Mainland China Financial Markets

Most studies in Mainland China focus on the relationship between domestic IS and local market dynamics from various angles. Shleifer and Summers (1990), Baker and Wurgler (2007), Han and Li (2017) constructed a Chinese market-based sentiment index and employed bias-reduction techniques to evaluate the return forecastability of IS. The findings showed that local IS in Mainland China was a reliable predictor of return for monthly horizon forecast. Global sentiment had spilled over to the local Chinese market, predicting negative future returns over longer time horizons and cross-sections. Wu et al. (2018) explored how IS influenced returns using the data of A-shares traded on the Chinese stock exchange market from 2006 to 2015. The results confirmed the positive impact of IS on experts' forecast bias. Chen et al. (2019) investigated the effects of internet finance IS on stock market returns using the database of monthly returns of all stocks listed in SSE from 2014 to 2017. The empirical results implied that the internet finance IS index has incremental forecast power of return comovement for stocks with larger market capitalization. Chen et al. (2020) examined the dynamic linking between IS and stock market-realized volatility using the price data of SSE and Shenzhen Stock Exchange (SZSE). To construct the IS index, they used five proxy variables *viz*., new stock accounts, turnover ratio, main balance, net active purchasing amount, and investor attention. They applied a two-step principal component analysis. The empirical findings indicated that IS could predict the market-realized volatility.

UAE Financial Market[14]

UAE is one of the important investment hubs within the GCC[15] and the Middle East. A strong focus on the diversification of economic activities, especially by Dubai and, recently, by Abu Dhabi, and a 5% value added tax (VAT) business environment have created an appealing atmosphere for investment in the UAE. The UAE has opened up its financial markets to foreign investors to promote economic growth to attract FDI and capital. Dubai and Abu Dhabi are the two most developed emirates in the UAE, and their economies rely on different sectors.

[14]The United Arab Emirates (UAE) is the Federation of seven Emirates: Abu Dhabi, Dubai, Sharjah, Ajman, Ras Al Khaimah, Fujairah, and Umm Al Quwain.

[15]Gulf Cooperation Council (GCC) comprises of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

While the emirate of Abu Dhabi is the major oil exporter in the UAE, and oil and gas have contributed 35% to its GDP, Dubai's oil contribution to GDP declined to nearly >1% at the end of 2018. Currently, the main revenues of Dubai are generated from non-oil sector activities, including tourism, real estate, trade, and financial services. Thus, the two financial markets—DFM and ADSE—operate under very different economic conditions and business environments (Kapar et al., 2020). There are very few studies analyzing investor behavior like India and Mainland China due to the lack of a well-defined proxy to measure IS in the UAE context.

Developed Financial Markets

Among the earliest studies that examine the relationship between IS on stock return in developed markets are Whaley (2000), Simon and Iii (2001), and Giot (2003), who use the volatility index (VIX) as an ideal measure of sentiment. Their results indicate a negative relationship between investor sentiment and stock return in major industrialized countries. Bathia and Bredin (2013) study reveals a negative relationship between investor sentiment and future returns of G7 nations. Uygur and Taş (2014) evaluate the returns and conditional volatility of various stock market indexes while considering changes in IS, and the results show that IS significantly affects conditional volatility in the US, Japan, Hong Kong, UK, France, Germany, and Turkey stock markets (Abdulmalek, 2021).

By using the S&P 500 composite index listed on the NYSE or NASDAQ, and using the VIX as a measure of sentiment, Smales (2017) finds a strong relationship between investor sentiment and stock returns, especially during the recession. Abdulmalek (2021) examined the relationship between IS and market volatility by using the S&P 500 index data and daily investors' indirect sentiment measures. The results indicate that the VIX volatility index is a more accurate fear indicator of market-wide IS and its ability to anticipate future volatility.

Nasir and Du (2018) empirically studied the Australian market in the context of the Stiglitz (2010) between 2003 and 2015, along with monthly data on nine top markets in the world in terms of capitalization. They concluded that the emerging markets, including Mainland China, Brazil, and India, showed a comparatively more significant impact on the UK financial sector, implying the increased importance of the UK financial sector during 2003-15.

Table 2 presents the bibliometric analysis of research in IS using Scopus data.

Table 3 presents the distribution of country/territory-wise studies done on IS.

Figure 1 visualizes the information from **Table 2** through a network of country/territorywise research work done on IS.

As seen in **Figure 1**, the work in the area of linkages between IS in the USA and its relationship with emerging markets is quite limited. Developed markets are described as efficient markets and characterized by a high degree of engagement from retail investors (Lee et al., 2002; Schmeling, 2009). **Figure 1** also demonstrates that fewer studies are conducted on emerging and frontier markets like India, Mainland China, and the UAE,

TABLE 2 | Key authors based on citations and TLS (total link strength).

#	Author	Citations	TLS	#	Author	Citations	TLS
1	Baker	2,350	27,478	8	Shleifer and Vishny, 2010	2,063	24,449
2	Barberis and Xiong, 2007	539	7,975	9	Stambaugh, 1999	497	8,443
3	Brown and Cliff, 2005	593	7,991	10	Statman, 2000	590	7,921
4	Fama, 2020	1,172	15,494	11	Subrahmanyam et al., 2016	712	10,094
5	French and Poterba, 1991	832	12,062	12	Titman, 1984	594	8,978
6	Hirshleifer, 2001	736	9,909	13	Wurgler, 2000	2,218	26,496
7	Odean, 2020	580	7,160				

Source: Authors' compilation using Scopus data.

TABLE 3 | Country/territory-wise work done on IS.

#	Country/territory	Articles	Citations	TLS	#	Country/territory	Articles	Citations	TLS
1	USA	530	25,435	8,651	8	India	106	464	817
2	Mainland China	328	3,532	3,265	9	France	61	737	679
3	UK	203	3,782	2,396	10	Tunisia	52	394	615
4	Taiwan	129	1,075	1,261	11	Canada	48	1,042	499
5	Germany	77	1,448	982	12	Hong Kong SAR	45	925	484
6	South Korea	71	919	918	13	Spain	50	537	433
7	Australia	102	1,533	903	14	Turkey	38	250	423
					15	Singapore	28	947	416

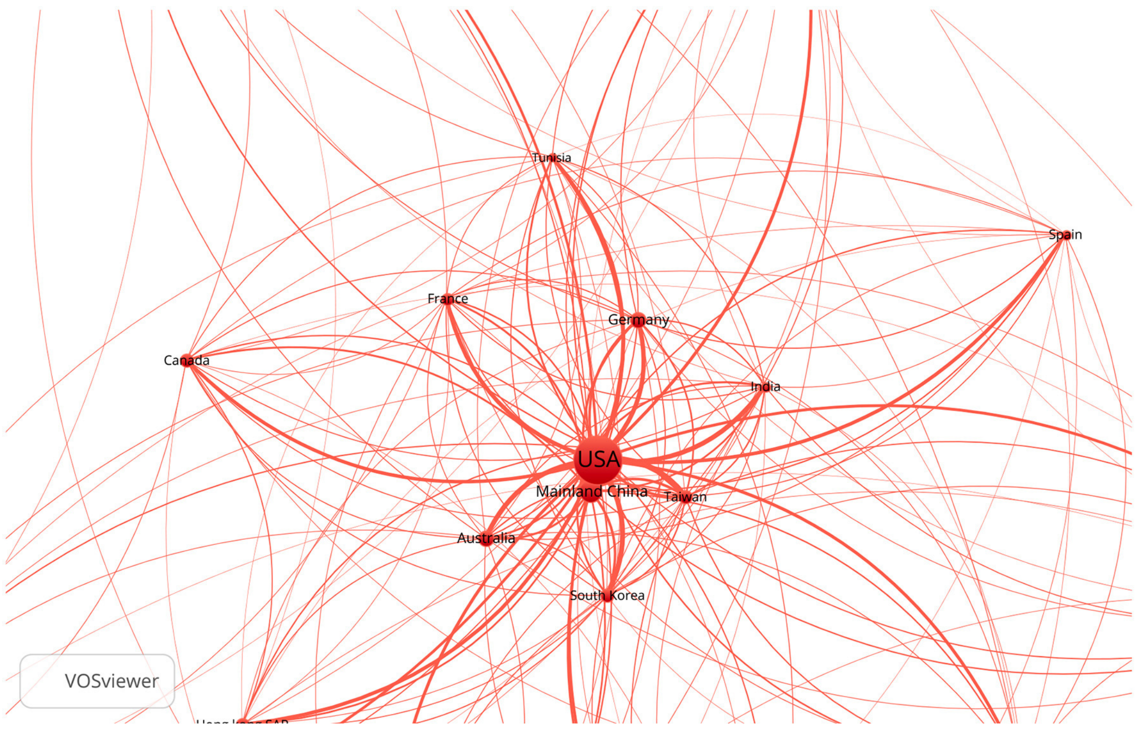


FIGURE 1 | Country/territory-wise work done on IS.

which are relatively described as inefficient markets. The stock market's inefficiency indicates institutional investors' lack of systematic arbitrage opportunities, providing a platform to assess the relationship of sentiment on the stock returns (Chakraborty and Subramaniam, 2020). Schmeling (2009) uses Consumer Confidence Index as a proxy for IS and shows that attitudes significantly influence less-developed markets with a lack of market integrity and are prone to herd-like behavior.

Wurgler and Baker (2006) use a top-down approach to develop a sentiment index based on six market proxies: closed-end fund discount, turnover, number of IPOs, first-day IPO returns, dividend premium, and equity issues. Siganos et al. (2014) use Facebook's daily sentiment proxy and find a positive contemporaneous relation to stock returns.

Recent Sentiment Approaches in Comparison With the Study

Chang et al. propose a novel method called correlation-based robust dynamic qualities (CBRDQ) to model the qualities of investor sentiments more accurately by considering the correlations among stocks. Authors refer to this quality measurement as dynamic quality since it assigns different qualities to the sentiments from a single user to different stocks. Based on a large-scale dataset from the real-world investor platform StockTwits, the authors evaluate CBRDQ and several conventional methods in a unifying stock recommendation framework. The results support the use of dynamic quality rather than static quality. Moreover, the comparative results demonstrate the method's effectiveness in making investment recommendations (Helleiner, 2011).

Li et al. propose a collective intelligence mechanism that can extract and consolidate the opinions expressed over the social investing platform and generate appropriate portfolios by analyzing other investors' knowledge, authority, and opinions about the investment target. The experimental results obtained based on the social investing platform eToro.com reveal that the portfolio recommended by the proposed mechanism outperforms the market index and other benchmark approaches in various financial performance aspects (Li et al., 2021).

Sachdeva et al. examine the motivators of herding behavior among investors, which cause speculative bubbles through a two-phase analysis. In the first phase, NVivo software was used to identify the factors driving herding behavior among Indian stock investors for text analysis. The analysis of a text was performed using word frequency analysis. While, in the second phase, the Fuzzy-AHP analysis techniques were employed to examine the relative importance of all the factors determined and assign priorities to the factors extracted. Results of the study depicted Investor Cognitive Psychology (ICP), Market Information (MI), and Stock Characteristics (SC) as the top-ranked factors driving herding behavior, while Socio-Economic Factors (SEF) emerged as the least important factor driving herding behavior. However, the limitation of the study is that the study was undertaken among stock investors from North India only. Moreover, numerous factors are not part of the study but might significantly influence the investors' herding behaviors (Sachdeva et al., 2021).

Zhang and Wang study whether network relevance exists between the investor's herding behavior and overconfidence behavior based on the complex network method. Since the investor's herding behavior is based on market trends and overconfidence behavior is based on past performance, the authors convert the time series data of market trends into a market network and the time-series data of the investor's past judgments into an investor network. Then, the authors update these networks as new information arrives at the market and show the weighted in-degrees of the nodes in the market network, and the investor network can represent the herding degree and the confidence degree of the investor, respectively. Using stock transaction data of Microsoft, US S&P 500 stock index, and China Hushen 300 stock index, the authors update the two networks and find that there exists a high similarity of network topological properties and a significant correlation of node parameter sequences between the market network and the investor network (Zhang and Wang, 2020).

Vukovi et al. compare the hybrid multiple criteria (equity market indicators, as well as financial indicators) decision-making (MCDM) approach to selecting the best stock to invest in the stock selection using modern portfolio theory (MPT- which includes only equity market indicators). The analyzed sample includes 18 stocks, which are CROBEX components on the Croatian capital market from January 2017 to January 2019. The rankings of stocks were calculated using five MCDM methods. These were then used to obtain the final hybrid stock ranking compared to the MPT stock selection. Their results show that the stocks, which have not entered any portfolio in MPT selection, were ranked as the lowest according to the hybrid MCDM approach, which confirms that those stocks are the worst to invest in Vuković et al. (2020).

Wu et al. propose a stock price prediction method that incorporates multiple data sources and investor sentiment, called S_I_LSTM. Firstly, the authors crawl multiple data, such as historical stock data, technical indicators, and non-traditional data sources, such as stock posts and financial news on the Internet, and pre-process them. Secondly, the authors use the sentiment analysis method based on a convolutional neural network for the non-traditional data, which can calculate the investors' sentiment index. Finally, the authors combine sentiment index, technical indicators, and stock historical transaction data as the feature set of stock price prediction and adopt the long short-term memory network for predicting the China Shanghai A-share market. The experiments show that the predicted stock closing price is closer to the true closing price than the single-data source, and the mean absolute error can achieve 2.386835, which is better than traditional methods. The authors verified the effectiveness of five listed companies (Wu et al., 2022).

Zhou et al. propose a field-aware attentive neural factorization machine (FAFM) model for large-scale data-driven company investment valuation. The proposed FAFM model utilizes a factorization machine (FM) to capture non-linear feature interactions in a sparse dataset efficiently. The authors additionally consider field heterogeneity among features with fuzzy mutual information and develop an attention NN to learn predictive strengths of pair-wise feature interactions. FAFM contributes to the literature by overcoming the limitation of FM that ignores field heterogeneity by factorizing pair-wise feature interactions with the same weight. Furthermore, FAFM learns the prediction strengths in a stratified manner using the attention deep learning mechanism, demonstrating a more structured control ability and allowing for more leverage in tweaking the interactions at the feature-wise level. Experiments are conducted on a unique real dataset set, consisting of 3,500 listed companies in the Chinese market with features from eight fields: demographics, annual reports, stock financial disclosure, land use, intellectual property, tax, bond financing, and certification. Results showed the superiority of FAFM on prediction accuracy and model interpretability over existing baselines. This study provides a useful tool for company investment valuation that can generate accurate investment valuations and provide interpretations of both individual features and the effects of their pair-wise interactions, thereby allowing investors better investment decisions (Zhou et al., 2022).

Huang et al. investigate individual investor sentiment on the Chinese stock message board Guba Eastmoney and its relation to the market returns and volatility. The authors focus on measuring the sentiment and propose a novel algorithm, Semantic Orientation from Laplace Smoothed Normalized Pointwise Mutual Information (SO-LNPMI). They show that: (i) compared to traditional methods, SO-LNPMI has higher accuracy and better adaptive property of probability estimate; (ii) negative sentiment is negatively correlated with market returns, whereas positive sentiment does not have any statistically significant impact on market returns; (iii) positive (negative) sentiment is negatively (positively) correlated with market volatility. Their results survive a range of robustness tests (Huang et al., 2022).

Why ANN Model Specification?

Since ANN grew out of the cognitive and brain science disciplines of Psychology, Neuroscience, and Engineering for approximating how information is processed and becomes insight, ANN facilitates adaptive learning as traders react to the news, learn, process information, and make decisions. The appeal of the ANN approach lies in its assumption of *bounded rationality*, wherein financial market participants are engaged in a learning process, continually adapting prior subjective beliefs from past mistakes. The basic idea is that reactions of economic decision-makers are not linear and proportionate but asymmetric and non-linear to changes in external variables. ANN approximates this behavior of economic and financial decision-making a very intuitive way. The financial sectors of emerging markets, but also in a market with a great deal of innovation and change, represent a fertile ground for using ANN for two interrelated reasons. One is that the data are often very noisy due either to the thinness of the market or to the speed with which news becomes dispersed so that some apparent asymmetries and non-linearities cannot be assumed away. Second, in many instances, the players in these markets are themselves learning, by trial and error, about policy news or legal and other changes taking place in the organization of their markets. The synaptic weights (parameters) estimated by the ANN, by which market participants forecast and make decisions, are themselves the outcome of a learning and search process (McNellis, 2005).

Other types of Neural Networks (Witten et al., 2017) are:

(a) Perceptron.
(b) Feed-Forward Neural Network.
(c) Multilayer Perceptron.
(d) Convolutional Neural Network.
(e) Radial Basis Functional Neural Network.
(f) Recurrent Neural Network.
(g) LSTM – Long- Short-Term Memory.
(h) Sequence to Sequence Models.

In our study, we have employed multilayer perceptron ANN, which includes elements of (a) and (b) for deriving synaptic weights. Using other NN in comparison, such as (d) to (h), is beyond the scope of the current study. This can be employed in future studies for comparing the NN performance.

Conceptual Framework

The expression "investor sentiment" includes the psychological attitude of investors toward the financial market. Specifically, IS explains the investors' tendency to speculate or the overall optimism or pessimism about an asset return when the economy encounters macro-level uncertainty, including economic crises and pandemic events like the recent COVID-19.

Figure 2 presents the comprehensive conceptual framework to address the research questions. The IS for India, Mainland China, and the UAE is the output (Y_{it}) to be predicted to attract investments from both domestic and foreign investors to finance healthcare sector initiatives. This is a key IS output measure in the framework. Respective country/territory market indices (SSE composite index in Mainland China, BSE-SENSEX in India, and MSCI-UAE) represent IS in these markets.

a. The inputs (X_{it}) are USA-IS captured through weekly American Association of Investors Surveys (AAIS). This weekly survey contains investor sentiments, such as bullish, bearish, neutral, spread, 8-week bullish moving averages, and S&P 500 returns for USA investors. Stocks traded and turnover ratio (Inputs X_{it}) represent investors' liquidity in Mainland China, India, and the UAE. These metrics are consistently used in earlier IS studies.
b. The framework also includes HDI as additional input (X_{it}), which has not been researched in earlier IS studies. Having a long and healthy life, being knowledgeable, and having a fair level of living are some of the most important aspects of human development that are measured by the Human Development Index (HDI). Normalized indexes for all three dimensions are averaged together to calculate the HDI. There are three dimensions to the health and education dimensions: life expectancy at birth, the average number of years spent in education for persons aged 25 and older, and the projected number of years spent in education for children beginning school. Gross national income (GNI) per person is a common way to gauge a country/territory's quality of life (http://hdr.undp.org).
c. Additionally, the framework includes Value Addition from Sectors (such as services, health sectors' value added in GDP) as Inputs (X_{it}) to reflect which sector is attractive to IS. Similarly, entrepreneurship is a key factor in the three economies that encourage innovation for self-employment

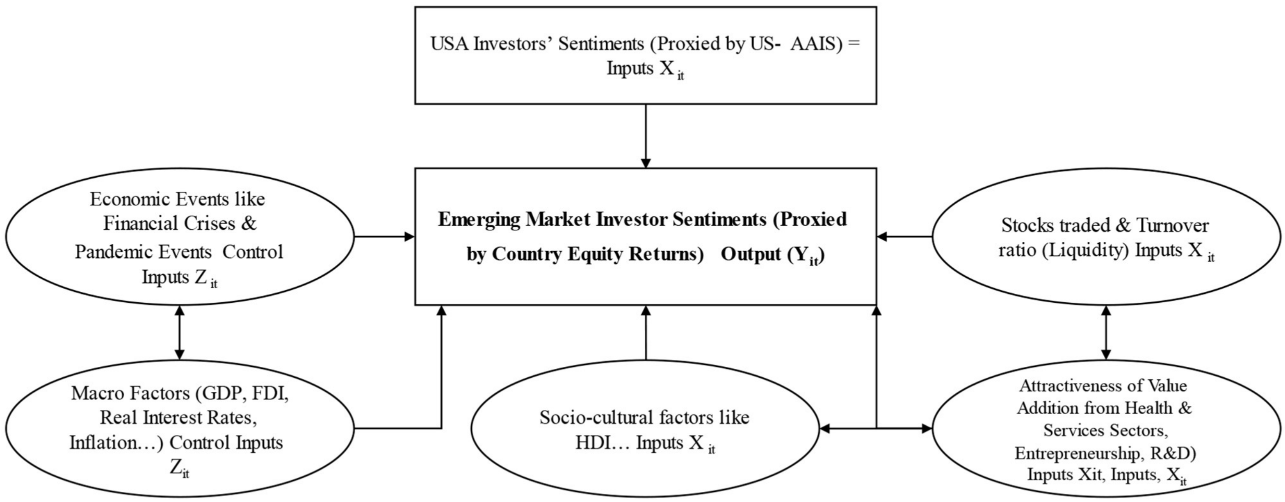


FIGURE 2 | Proposed conceptual framework.

and R&D in terms of published research articles. It is interesting to note their importance and impact on IS.

d. Control inputs (Z_{it}), including economic events like the financial crisis in 2008-09, pandemics from 2000-2020, including COVID-19, we believe have a greater herd-like and uncertain impact on IS in Mainland China, India, and the UAE.

The importance and the impact of the factors detailed under b, c, and d have not been thoroughly studied by researchers in earlier IS studies to attract investments from both domestic and foreign investors to finance healthcare sector initiatives to reduce UHC.

e. Consistent with earlier studies with mixed results, our framework includes macro factors (like GDP growth, inflation, real interest rate…) as control factors (Z_{it}) for analyzing their importance on IS.

METHODOLOGY AND DATA

Empirical Model (Logistic Regression)

Equation (1) represents the empirical model used to evaluate the conceptual framework.

Emerging Market Return $(R_{kt})(\frac{1}{0}) = \alpha_{it} + \beta_{kt(1\text{-}3)}$ US Investors Sentiments$_{it(1\text{-}3)}$ $+\beta_{4t}$ US Market Return $+\beta_{5t}$ US Market Spread$_{5t}$ (Proxy for variability) $+\Omega_{jt}$ Sectoral and HDI Variables$_{jt}$ $+\ \theta_{jt}$ Countries Macro-Economic Variables$_{jt}$$+\ \pi_{jt}$ Crises and Pandemic events $+ + \varepsilon_t \rightarrow$ Equation (1).

In Equation (1),

$R_{kt}[= (P_t\text{-}P_{t-1}) \div (P_{t-1})]$ is the return of country/territory k at Week t, (1 denotes positive returns and 0 denotes negative returns);

Sentiment$_t$ is the value of the USA sentiment measures (bullish, neutral, bearish, spread, and 8-week bullish moving average) at time t;

β_{kt} is logistic regression coefficients on USA return and spread/variability measure impact for country/territory k in time t;

Ω_{jkt} is the logistic regression coefficients on j sector and HDI factors for country/territory k in time t.

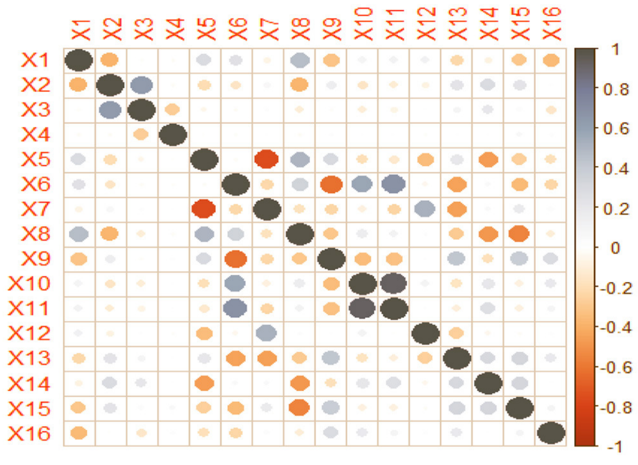
θ_{jkt} is the logistic regression coefficients on j macro-economic indicators for country/territory k in time t.

π_{jkt} is the logistic regression coefficients on j crises and pandemic events for country/territory k in time t;

ε_{kt} is the error term for country/territory k in time t.

Thus, the conceptual framework in **Figure 3** is quite comprehensive and encompasses many behavioral factors related to SDG-3 (health and well being) and SDG-8 (growth and economic development) captured by sociocultural crises and pandemic events in particular, and other sectoral value-added and macro-economic variables in general. Thus, instead of focusing on hypotheses, the study tries to capture the importance of the behavioral factors in IS modeling by applying AI tools through ANN. **Table 4** summarizes the variables used in Equation (1).

The data set covering the above variables was partitioned randomly, with 50% for training and 50% as a testing set. To start with, traditional logistic regression is employed using Equation 1 on the test sample to perform the empirical analysis of examining the importance of behavioral variables besides the USA IS for each of the three countries. Classification algorithms, such as logistic regression in R Programming, are commonly used to determine the likelihood of an event's success or failure. The dependant variable in logistic regression is a binary one (0/1, true/false, yes/no). A binomial distribution's link function is the logit function. Therefore, one of the names for logistic regression is the Binomial logistics regression. It is based on the sigmoid function where output is probability and input can be from -infinity to +infinity. In theory, logistics regression is also known as



Code	Predictor	Code	Predictor	Code	Predictor	Code	Predictor
X1	Neutral	X5	HDI	X9	POP-G annual %	X13	FDI NI%GDP
X2	8-week BMA	X6	CHE %GDP	X10	STOCKS-TRADED VALUE (%GDP)	X14	GDP-AG%
X3	Spread	X7	ANEMIA	X11	STOCKS-TRADED-TO-D (%)	X15	INF-A%
X4	USA Returns	X8	SER-VA%GDP	X12	Real Interest rate%	X16	EC-PE CODE

FIGURE 3 | Correlation between remaining 16 predictors.

a generalized linear model. As it is used as a classification technique to predict a qualitative response, the Value of Y ranges from 0 to 1.

MODEL RESULTS

Preliminary Exploratory Analysis

We excluded 12 predictors from further model experimentation as they were highly correlated (such as bullish, bearish, *per capita* CHE, Internet%, industry-VA, manufacturing-VA, AFF-VA, SET, SEM, SEF, PRJ R&D, and GNI *per capita*) with other predictors.

Figure 3 shows no significant correlation between the remaining 16 predictors, as can be seen from the size of the bullets. They will be used for Logistic and ANN model experiments.

Logistic Regression Results

Table 5 presents the logistic regression results on the pooled test sample data.

In the logistic regression, the USA Sentiment predictors (neutral, bullish moving average, and spread) were positively related to IS but were not significant in predicting emerging markets' IS. USA stock market return (X_4) is negatively associated with emerging market investors' IS in respective countries and is very highly significant at $\alpha = 0.00001$. This implies that the emerging market investors negatively responded to the increase in US market returns and preferred to invest in their respective countries' markets. If USA market returns are low, emerging market investors would prefer to invest in their respective markets to get higher returns.

Regarding health sector impact on IS, none of the three health predictors (HDI-X_5, CHE as % of GDP-X_6, anemia reflecting nutrition status of the population-X_7) influenced investors' sentiments. This implies that domestic investors are not keen to invest in health sector initiatives to support UHC of the respective countries, reflecting the higher level of market inefficiencies in terms of asymmetric information in these markets. However, these results were not statistically significant.

As regards to economic fundamentals:

- The higher performance of the services sector as value added in the country/territory's GDP (X_8), the investors would prefer to invest less in these service sectors, and the result is highly significant at $\alpha = 0.002$. Components of service sectors include health; economic service and social service; transport, storage, and communication; trade, hotels, and tourism; banking and insurance services; education; and administration. This observation complements the previous health sector's impact that domestic investors do not have positive sentiments in these sectors to make their investments, probably due to market and sectoral inefficiencies in their economies.
- The higher stock value in $ terms traded (X_{10}) in the respective markets reflects the financial markets' liquidity. Hence, under the pretext of liquidity preference, the domestic investors would have positive sentiments to invest their surpluses in deriving higher returns in their economies for liquidity reasons. The predictor's result is positively related to domestic investor sentiments and is highly significant at $\alpha = 0.000000195$.
- On the other hand, higher stock turnover relative to domestic shares (X_{11}) occurs due to domestic and foreign institutional

TABLE 4 | A list of variables.

		Time	Period = Jan 2003 to December 2020	What the variable represents?	Frequency	Source
			Country/territory	3 fast-growing economies		
Code	Variable name	Input	Country/territory code (k)	Mainland China (C=1), India (I = 2), UAE (U = 3)		
Y_1 Y_2 Y_3	Country/territory returns -IS	Country/territory outputs	$Y_{kt} = R_t = (P_t\text{-}P_{t-1}) \div P_{t-1}$	Investor weekly return in C, I, U	Weekly	C=Shanghai[a] I = BSE-SENSEX[b] U=MSCI- UAE[c]
X_i	USA-IS	Input	AAIS[d] sentiment readings	US investor sentiments	Weekly	Bloomberg
X_5	Spread[e]	Input	Measure of variability	Difference between bullish and bearish sentiments	Weekly	Bloomberg
X_6	USA Return	Input	SandP 500	Market return for the US	Weekly	Bloomberg
Socio-cultural development indicators						
X_{7k}	HDI	Input	Human development indicator	Geometric mean of average achievement in 3 key dimensions of human development[f]	Yearly	http://hdr.undp.org/en/data
X_{8k}	GNI*		Gross national income	Per capita - PPP constant 2017 international $) - Do the investors have investing capacity?	Yearly	World Bank
X_{9k}	POP-G*		Population growth annual % -	Life style and values that characterize the society	Yearly	World bank
Sectors - value added (VA) as % GDP in achieving UN SDG 3 (Health and Wellbeing) and SDG 8 (Growth and economic development)						
X_{10k}	CHE*	Input	Percapita CHE $ - health sector	Current health expenditure by the governments - UN SDG 3	Yearly	World bank
X_{11k}	CHE %GDP	Input	CHE %GDP - health sector	CHE as percentage of GDP - UN SDG 3	Yearly	World bank
X_{12k}	Anemia	Input	- Health sector - nutrition	Prevalence of Anemia in children < 59 months - UN SDG 3	Yearly	World Bank
X_{13k}	Internet*	Input	INTERNET% - technology sector - life style	Penetration of internet in the population- UN SDG 8	Yearly	World bank
X_{14k}	Ind-VA*	Input	Industry VA-% GDP - industry sector	Industry value added (VA) in GDP (%) -UN SDG 8	Yearly	World bank
X_{15k}	Mfg-VA*	Input	MFG-VA%GDP - manufacturing sector	Manufacturing value added (VA) in GDP (%) -UN SDG 8	Yearly	World bank
X_{16k}	Ser-VA	Input	SER-VA%GDP - services sector	Services value added (VA) in GDP (%) -UN SDG 8	Yearly	World bank
X_{17k}	Aff-VA*	Input	Agriculture, fishery, forestry (AFF) sectors	AFF value added (VA) in GDP (%) -UN SDG 8	Yearly	World bank
X_{18k}	Prj-RandD*	Input	PRJ-RandD - Peer reviewed journals #	Productivity through RandD investment - UN SDG 8	Yearly	World Bank
X_{19k}	SET*	Input	SET% - SME sector - Entrepreneurs	Self employed - total % - UN SDG 8	Yearly	World bank
X_{20k}	SEM*	Input	SEM% - SME sector - male	Self employed - male entrepreneurs % - UN SDG 8	Yearly	World bank
X_{21k}	SEF*	Input	SEF% - SME sector - Female	Self employed - Female entrepreneurs % - UN SDG 8	Yearly	World bank
X_{22k}	STV*	Input	Stocks traded value (%GDP)-	How active and liquid the stock market in C, I, U is for investors	Yearly	World bank
X_{23k}	ST-TO	Input	Stocks traded-turnover - Domestic (%) - Micro variable - Firm specific	How liquid is the stock market in the domestic market in C, I, U for Investors	Yearly	World bank
Macroeconomic factors (Z_k)						
Z_{1k}	RIR	Control input	RIR-Real Interest rate%	How attractive is the Risk Free Rate in C, I, U to the investors?	Yearly[g]	World bank
Z_{2k}	FDI-NI	Control input	Foreign Direct Investment Net Inflow as %GDP	How attractive is the investment environment to overseas investors which impacts IS in C, I, U	Yearly	World bank

(Continued)

TABLE 4 | Continued

		Time	Period = Jan 2003 to December 2020	What the variable represents?	Frequency	Source
Z_{3k}	GDP-AG	Control input	GDP-AG%	GDP - annual growth % - Is the growth attractive for investors?	Yearly	World bank
Z_{4k}	INF	Control input	INF-A%	Inflation - Annual % - Is it too high and unattractive for the investors?	Yearly	World bank
Economic crises (EC) and pandemic events (PE) (Z_k)						
Z_{5k}	PE-EC	Control input	Economic Crises (EC) Pandemic Event (PE) EC-PE CODED as PE = 1, EC = 2, None = 0	How the events affected the sentiment of investors? EC - sub-mortgage crises in 2007-09 in C, I, U PE - includes the following pandemic events in C, I, U: - SARS in 2002-04 - EBOLA in 2004 - Dengue in 2006 - Swine Flu in 2010 - Zika in 2015-16 - Covid in 2019-20	Yearly	WHO

** All the variables marked with an asterisk were excluded from further modeling as they were highly correlated (Rho > 0.6).*
[a] https://www.macrotrends.net/2592/shanghai-composite-index-china-stock-market-chart-data
[b] Bloomberg.
[c] MSCI-MEA-UAE.
[d] American Association of Individual Investors Survey i = 1 = Bullish (% of people in the survey who are bullish (for US markets); 2 = neutral (% of people in the survey who are neutral); 3 = bearish (% of people in the survey who are bearish); 4 = 8 week moving average of bullish indicator (BMI).
[e] The difference between bullish and bearish USA-IS sentiment in the AAII survey.
[f] The HDI uses the logarithm of income to reflect the diminishing importance of income with increasing GNI. The scores for the three HDI dimension indices are then aggregated into a composite index using geometric mean.
[g] For UAE, Weekly Real Interest rates were obtained from UAE Central Bank for 2006-2020. For early years, the data were extrapolated by taking the geometric 8-week moving average.

investors (FII) looking for short-term gains. In such a case, the domestic markets are bearish in their sentiments since they are individual investors and would not be able to invest in the volume required to significant such short-term gains, unlike FIIs. Therefore, the predictor's result is negatively related to domestic investor sentiments and is highly significant at $\alpha = 0.00000000785$.

As regards to macro-economic fundamentals:

- As expected, FDI inflows (X_{13}) are positively related to market returns. But this is less significant at $\alpha = 0.085$.
- As expected, domestic GDP growth (X_{15}) is negatively related to domestic investors' sentiments, and this relation is statistically very highly significant at $\alpha = 0.00014$. This is because higher inflation reduces the purchasing power of the domestic currency, and there is less money surplus left with the investors. Hence, there is no motivation for such investors to invest in their markets to earn higher returns.

As regards to economic crisis and pandemics in their economies:

- Unexpectedly, the domestic investors' sentiments are negatively related to these uncertain events. However, this relationship is statistically insignificant.

Table 6 shows the confusion (or classification accuracy percentages) matrix, which is a key diagnostic for IS classification to derive positive returns (coded as 1) or negative returns (coded as 0). The total classification prediction percentage is 65.95%. Typically, one would have expected around 70% and above to say that the logistic prediction model is reasonable for prediction purposes.

Similar results are seen from the ROC curve in **Figure 4**.

TABLE 5 | Logistic regression coefficient estimates the pooled test data (*N* = 1022; *50% of the training set*).

##		Estimate	Std. Error	z value	Pr(>|z|)	
##	(Intercept)	1.452313	1.902078	0.764	0.445141	
##	X1	0.228796	0.946877	0.242	0.809065	
##	X2	0.390072	1.055958	0.369	0.711829	
##	X3	0.261754	0.438545	0.597	0.550595	
##	X4 USReturn	s-0.243153	0.02893	−8.405	< 2e-16	***
##	X5	1.861368	1.741276	1.069	0.285084	
##	X6	0.188705	0.215447	0.876	0.381097	
##	X7	0.00345	0.012209	0.283	0.777499	
##	X8 SER-VA	−0.071712	0.023155	−3.097	0.001955	**
##	X9 POP.G%	0.085167	0.030173	2.823	0.004763	**
##	X10Stock-$	0.013934	0.002677	5.204	1.95E-07	***
##	X11Stock-TO	−0.013222	0.002291	−5.772	7.85E-09	***
##	X12	0.016676	0.030418	0.548	0.583535	
##	X13FDI-NI%	0.133416	0.077663	1.718	0.085817	.
##	X14	0.01016	0.020994	0.484	0.628424	
##	X15INF-A%	−0.052275	0.013722	−3.81	0.000139	***
##	X16	−0.047028	0.110094	−0.427	0.669258	

*## Significance.codes: 0 "***" 0.001, "**" 0.01, "*" 0.05, '.' 0.1, AIC = 2275.6; AUC 0.6132.*

TABLE 6 | Logistic regression confusion matrix.

	Predict_reg		Total	% correct
	0	1		
0	124	189	313	39.62
1	82	401	483	83.02
Total	206	590	796	65.95

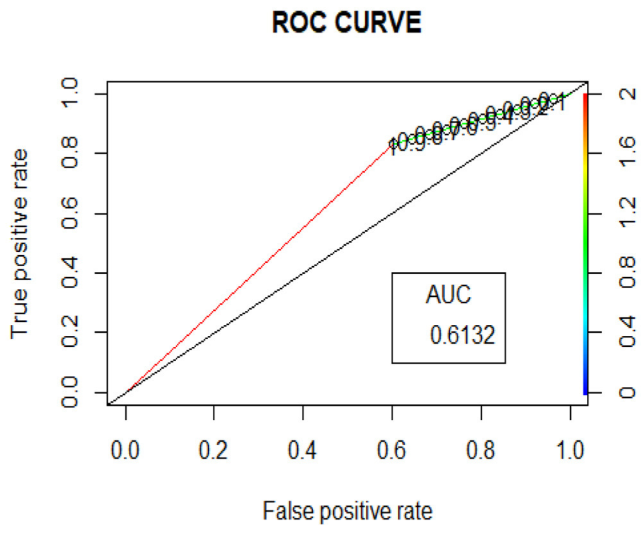


FIGURE 4 | ROC curve in logistic regression.

We now extend the pooled logistic analysis country/territory-wise to know each country/territory's results. Will it be similar to the pooled results? Are they diverging from it country/territory-wise?

Logistic Results for Mainland China

From **Table 7**, in Mainland China:

- USA-Neutral sentiments positively impact Mainland China IS but are less significant at $\alpha = 0.03675$.
- Unexpectedly, the health predictor Anemia negatively impacted Mainland China's IS and is highly significant at $\alpha = 0.00163$. This implies that Mainland China investors were not keen to invest in health sector initiatives to support UHC.
- Expectedly, the higher stock traded in $ terms. Mainland China investors were optimistic about investing in SSE. This result is highly significant at $\alpha = 0.000982$, implying the investors sensed liquidity in their investments.
- Similar to pooled results, Mainland China investors responded negatively to high stock turnover in SSE, and the impact is highly significant at $\alpha = 0.0000939$.
- Mainland China investors responded negatively to Mainland China's real interest rate. However, the result is less significant, $\alpha = 0.0901$, implying that Mainland China's SSE investment is preferred as they were optimistic about higher returns from SSE investments.
- The higher GDP growth, Mainland China investors were bullish to invest in SSE and is significant at $\alpha = 0.0587$.
- Similar to pooled results, Mainland China investors were bearish during high inflation scenarios and are significant at $\alpha = 0.02662$.
- Unexpectedly, Mainland China investors were bullish on economic crisis and pandemic events and still invested in SSE with the expectation of higher returns. The result is significant at $\alpha = 0.04862$.
- From **Table 8**, the model classified correctly 49.81% of Mainland China IS as seen from the following:

TABLE 7 | Logistic regression results in Mainland China.

##		Estimate	Std. Error	z value	Pr(>|z|)	
##	(Intercept)	11.443834	7.496909	1.526	0.12689	
##	X1 Neutral	3.538716	1.694338	2.089	0.03675	*
##	X2	2.677745	1.931124	1.387	0.16556	
##	X3	0.246615	0.762399	0.323	0.74634	
##	X4	−0.061211	0.04586	−1.335	0.18196	
##	X5	−0.915878	5.260397	−0.174	0.86178	
##	X6	0.768442	1.129804	0.68	0.49641	
##	X7 Anemia	−0.436799	0.13862	−3.151	0.00163	**
##	X8	−0.117967	0.114474	−1.031	0.30277	
##	X9	0.639194	1.618424	0.395	0.69288	
##	X10 Stock($)	0.010539	0.004082	2.582	0.00982	**
##	X11 StockTO	−0.015996	0.004095	−3.906	9.39E−05	***
##	X12 Int%	−0.539479	0.318212	−1.695	0.09001	.
##	X13	0.232462	0.319204	0.728	0.46646	
##	X14 GDPG%	0.173987	0.091951	1.892	0.05847	.
##	X15 INF%	−0.687477	0.310093	−2.217	0.02662	*
##	X16 EC-PC	0.695205	0.35255	1.972	0.04862	*

*## Significance codes: 0 "***" 0.001, "**" 0.01, "*" 0.05, "." 0.1, 1.*
AIC 821.19 (AUC = 0.49).

TABLE 8 | Logistic regression confusion matrix (Classification %).

	Predict_reg		Total	% correct
	0	1		
0	71	60	131	54.20
1	72	60	132	45.45
Total	143	120	263	49.81

Logistic Results for India

From **Table 9**, in India:

- Investors were bearish to USA BMA sentiments, implying that, if the USA market is bullish, they were skeptical that BSE-SENSEX would be bullish due to India's international non-spillover effect (contagion). The result is highly significant at $\alpha = 0.020401$.

TABLE 9 | Logistic regression results in India.

##		Estimate	Std. Error	z value	Pr(>|z|)	
##	(Intercept)	−27.708823	39.907677	−0.694	0.48748	
##	X1	−2.405275	1.951105	−1.233	0.21766	
##	X2 BMA	−4.769608	2.056991	−2.319	0.02041	*
##	X3 Spread	1.40793	0.834883	1.686	0.09172	.
##	X4 USA Return	−0.473923	0.065637	−7.22	5.18E-13	***
##	X5	4.227747	13.763152	0.307	0.75871	
##	X6	1.995532	1.388599	1.437	0.15069	
##	X7	0.369218	0.572299	0.645	0.51883	
##	X8	0.120278	0.312827	0.384	0.70062	
##	X9	−6.423619	11.397568	−0.564	0.57303	
##	X10 Stock $	0.042617	0.013313	3.20E+00	0.00137	**
##	X11	−0.009769	0.013629	−7.17E-01	0.4735	
##	X12	−0.084035	0.269087	−0.312	0.75481	
##	X13	−0.014422	0.399822	−0.036	0.97123	
##	X14	0.156786	0.126885	1.236	0.21659	
##	X15	−0.06254	0.373857	−0.167	0.86715	
##	X16	−0.184757	0.254841	−0.725	0.46846	

*## Signif. codes: 0 "***" 0.001, "**" 0.01, "*" 0.05, ''.'' 0, 1.*
AIC = 715.8; AUC = 0.6871.

TABLE 10 | Logistic regression confusion matrix (classification %).

	Predict_reg		Total	% correct
	0	1		
0	60	54	114	52.63
1	21	117	138	84.78
Total	81	171	252	70.24

- On the other hand, if USA Spread sentiment is highly variable, Indian investors were bullish in investing in BSE-SENSEX as they believed that variability in India would be low due to the international non-spillover effect (contagion) in India. The result is less significant at $\alpha = 0.09172$.
- Consistent with the above results, if the USA market return is lower, for the same reason of international non-spillover effect (contagion), Indian investors were bullish on investing in BSE-SENSEX. The result is very highly significant at $\alpha = 0.000000000000518$.
- If the Stock traded in $ in BSE-SENSEX was higher, the Indian investors were bullish on investing in BSE-SENSEX due to liquidity preference. The result is highly significant at $\alpha = 0.00137$.
- Unfortunately, none of the health, macro factors, and pandemic events impacted Indian IS plausibly due to asymmetric information and market inefficiencies in the Indian market. The model classified correctly 70.24% of Indian IS as seen from **Table 10**.

TABLE 11 | Logistic regression results in the UAE.

##		Estimate	Std. Error	z value	Pr(>|z|)	
##	(Intercept)	31.64525	12.09715	2.616	0.0089	**
##	X1	1.53461	1.78821	0.858	0.3908	
##	X2	−0.90936	1.9857	−0.458	0.647	
##	X3	−0.12035	0.78096	−0.154	0.8775	
##	X4 USAReturn	−0.20833	0.0471	−4.424	9.71E-06	***
##	X5	−8.79685	13.97404	−0.63	0.529	
##	X6 CHE%GDP	0.91755	0.55459	1.654	0.098	.
##	X7 Anemia	−1.22068	0.52801	−2.312	0.0208	*
##	X8	−0.0744	0.05335	−1.395	0.1631	
##	X9 Pop-G%	−0.19701	0.09749	−2.021	0.0433	*
##	X10	0.04053	0.07093	0.571	5.68E-01	
##	X11	−0.01254	0.03577	−0.351	7.26E-01	
##	X12 Int%	0.4887	0.2499	1.956	0.0505	.
##	X13	0.24044	0.17051	1.41	0.1585	
##	X14	−0.08414	0.05484	−1.534	0.125	
##	X15	0.01297	0.01803	0.719	0.4719	
##	X16 EC-PE	0.50592	0.28883	1.752	0.0798	.

*## Signif. codes: 0 "***" 0.001, "**" 0.01, "*" 0.05, "." 0.1. 1 AIC = 746.88; AUC = 0.498.*

Logistic Results for the UAE

From **Table 11**, in the UAE:

- Investors were not responsive to USA sentiments, as seen from the insignificant statistic for Neutral, BMA, and Spread Predictors.
- Similar to India's results, if the USA market return was lower due to the international non-spillover effect (contagion), the UAE investors were bullish on investing in either DFM/ADSE. The result is very highly significant at $\alpha = 0.000000971$.
- If current health expenditure (CHE) as a percentage of GDP increased, the UAE investors were bullish on investing in DFM/ADSE. Section Healthcare Trends Post COVID-19 of this research article shows that the UAE is placed in the highly developed category under HDI by UNDP. Good Health and Wellbeing is one of the components of HDI. Hence, the UAE investors are bullish on investing in their markets if the CHE% GDP increases due to proactive steps taken by the UAE Health authorities. The result is, however, less significant at $\alpha = 0.098$.
- Like Mainland China IS, the UAE health predictor Anemia negatively impacted the UAE IS and is significant at $\alpha = 0.0208$. This implies that the UAE investors were not keen to invest in health sector initiatives to support UHC if the UAE population's nutrition status was weak. The result is significant at $\alpha = 0.0208$.
- The higher UAE real interest rate – the UAE investors were bullish and invested in DFM/ADFM with the optimism of getting a higher return from their investments. The result is significant at $\alpha = 0.0505$.
- Unexpectedly, similar to Mainland China investors, the UAE investors were bullish on economic crisis and pandemic events and still invested in DFM/ADFM with an expectation of higher returns. The result is significant at $\alpha = 0.0798$.

TABLE 12 | Logistic regression confusion matrix (classification %).

	predict_reg		Total	% correct
	0	1		
0	4	58	62	6.45
1	15	204	219	93.15
Total	19	262	281	74.02

TABLE 13 | A summary of model parameters *(3-layer-neural network)*.

Model	Artificial neural network
Layers	3-Hidden, 1-input, and 1- output layer
Activation function	ReLu (Rectified Linear Unit) *Y= f(x) = max{0,x}*
Learning rate	0.001 (Lower the value more the scope for learning)
Optimizer used	SGD (Stochastic Gradient Descent)
Loss model	Binary cross entropy
Epoch	500
Batch size/step size	16/35

Unfortunately, similar to India's results, none of the macro factors impacted the UAE IS plausibly due to market inefficiencies in the UAE market, which is well documented by Rao (2005).

The model classified correctly 74.02% of the UAE IS, as seen from **Table 12**.

As seen from **Tables 10**, **11**, **13**, each country/territory's results in the logistic model differed widely from the pooled logistic model results, and the prediction accuracy is not consistent across countries. Let us see whether this result differs in the ANN modeling.

ANN Model Architecture and Results

Machine learning algorithms are substantial when the dataset is around a small or medium scale. As the dataset grows, the inference yielded by the machine learning models tends to be error prone. Due to this, the researchers tend to prefer Neural Networks over traditional ML models for a medium to the large dataset. Neural Networks are internally designed to learn from data recursively using a back propagation algorithm and proved to be superior to ML algorithms when the feature set and population sample are high. A neural network can be vaguely visualized as a sequential bunch of nodes wired together in a way where each node performs mathematical operations on the incoming signal before passing the signal on to the next node, a concept derived from the biological neuron of the human brain. Blatant minimalistic neural networks comprise of three layers; they are:

1. ***Input layer***—The input features are mapped to input nodes along with the weight here.
2. ***Hidden layer***—The output of the input layers fed into the hidden layer, which comprises its own activations that push the Hidden node's output to the next hidden layer. Depending upon the choice of users and the iterations to run, the number of hidden layers can be increased or decreased.
3. ***Output layer***—the output of the hidden layer can be aggregated in this layer. The number of nodes in the output layer depends on the number of classes (binary/multiclass).

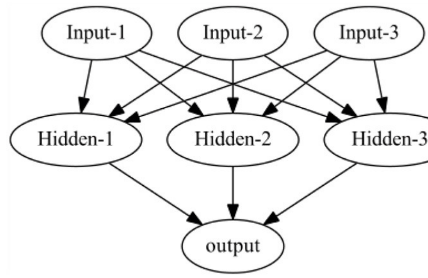


FIGURE 5 | A simple perceptron model with a 1-hidden layer.

A simple 1-layer Neural Network is depicted below in **Figure 5**. It consists of 1 input, hidden, and output layer.

The order of the neural network layer is sequential: the input layer, the n-hidden layer, and, finally, the output layer. The input to the neural networks can be numerical, images, text data, or data in an encoded format, but mathematical computation usually happens in the hidden layer rather than at the input layer. Each hidden layer node comes with a computational unit that applies a function on the incoming data and an activation function that sets criteria to decide whether the learning at the node is passable or rejected. The hidden layer is quintessential because the complex relationship between input and output values is identified here, and important features are learned at each node. The activation function at each node decides the output value at the node. Some of the commonly used activation functions are LeakyReLu, ReLu, Tanh, Sigmoid, etc. Each of them has its own use case and can be tried out on a need basis.

The purpose of the activation function is to add a non-linearity nature to the learning model to avoid bias, which, in turn, helps to determine the complex relationship between the input features and the target variables. Some of the commonly used activation functions are:

1. Sigmoid activation function: Sigmoid activations are basically used for the scenarios under binary classification. The output is regulated between the values 0 and 1 so does its probability. The mathematical function for sigmoid is:

$$y(x) = \frac{1}{e^{-x}}$$

Where y (x) = prediction y is generated for every value of x.

2. Tanh activation function: The Tanh activation value ranges from −1 to 1. The activation is preferred when one wants to center the data on zero for better learning. The mathematical function for tanh is:

$$y(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

TABLE 14 | ANN confusion (classification) matrix—pooled data.

		Predicted		T	% correct
		1	0		
Actual	1	140	70	210	0.67
	0	99	220	319	0.69
	T	239	290	529	0.68

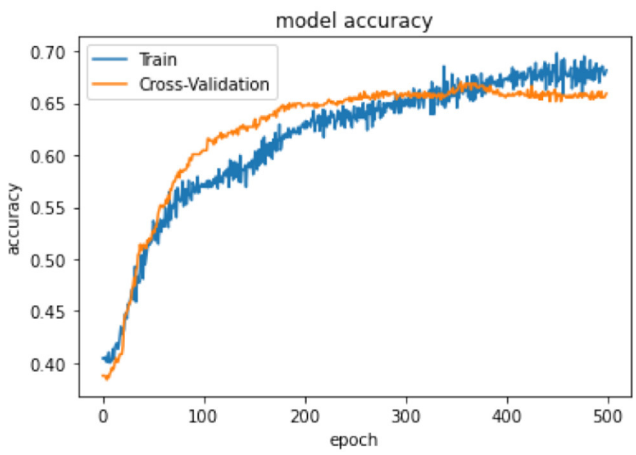


FIGURE 6 | ANN model accuracy pooled set.

1. ReLU activation function: ReLu activation is the most preferred activation function for dense neural networks and convolutional neural networks since it has the power to extract useful information suppressing noise in the data. The mathematical function for ReLu is:

$$y(x) = \max(0, x)$$

2. Softmax activation: SoftMax is an activation function that is used in the output layer, as well as in hidden layers. In this activation, the probability scores of each class are given in the output nodes such that the sum of the probability score is equal to one. The mathematical function for Softmax is:

$$y(x) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

On the other hand, optimizers are methods to customize the neural network parameters, such as learning weights, learning rate, error rate, and bias to reduce the overall loss. Some of the commonly used optimizers for the neural networks are as follows:

1. Gradient descent: The gradient descent algorithm depends on the first-order derivative of the loss functions. The weight is recomputed upon back propagation of the loss at every node, which depends on the first-order derivative. The weights are stabilized once the loss model function descends to a local minima.

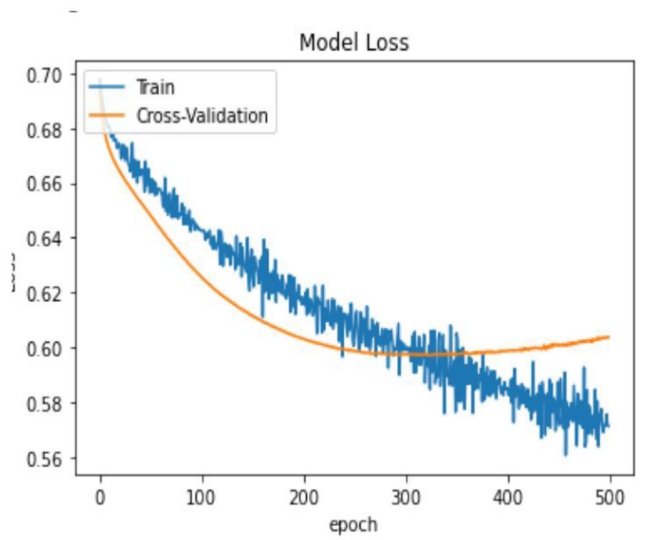


FIGURE 7 | ANN model loss pooled set.

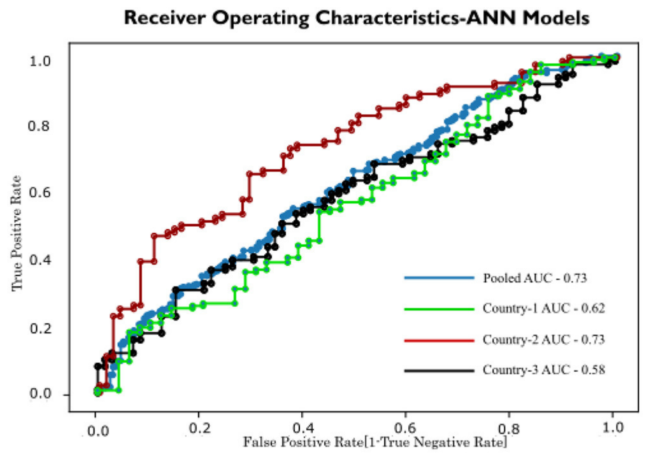


FIGURE 8 | ANN ROC curve.

2. Stochastic gradient descent (SGD): A variant of the Gradient descent method, where it converges to local minima by performing several iterations of updates quickly.
3. Adam optimizer: This optimizer emphasizes slowing down computation and considers every local minimum along the path, ensuring the correct learning at the cost of speed and time.
4. Mini-batch gradient descent: Another commonly used optimizer is an upgrade of SGD method, and it updates the model parameters in batches instead of updating individuals. This optimizer is faster compared to SGD and converges to minima more rapidly than SGD.

Experimental test bed:

A series of experiments were conducted to observe the behavior of the Neural Network models over the dataset rigorously and concluded that 3-Layer Neural networks were suitable for the dataset. Several activation functions were tested, such as sigmoid, Tanh, ReLu, and LeakyReLu. Some of the notable model parameters are listed below in **Table 13**.

We applyied ANN for the same set of 16 predictors with the same number of the test sample (i.e., 50% of the training set) used in Logistic regression to see if the ANN model predicted IS better than the Logistic Model. The following steps were followed for building the ANN model:

- Step 1. Sample the dataset randomly and return fraction (e.g., frac = 50% will return 50% of the data) from the dataset.
- Step 2. Split the data into train/test splits.
- Step 3. Class = Class variable (1: positive market return, 0: negative market returns for respective countries).
- Step 4. We will move the Class variable from each dataset split (train, test, validate) and save it into new variables. In this step, we maintain the order of the labels and data from now on to make sure each example/row is associated with the right label.
- Step 5. Data curation: Data are normalized/scaled by subtracting the mean from the training data and dividing it by the standard deviation of the training data.
- Step 6. Build an ANN model (the algorithm is kept with us and will be made available if needed).
- Step 7. Training the model that we built above.
- Step 8. See how the training went by plotting the accuracy/loss across epoch and confusion matrix.

In terms of model performance, training accuracy is 0.71, evaluation accuracy is 0.63, and validation accuracy is 0.68. Our pooled set model accuracy, model loss, and confusion performance are as below with 3 layers in the ANN architecture using the SGD optimizer with Binary cross Entropy as a loss model.

In **Table 14**, the classification percentage has improved to 67% for positive IS returns in the test sample, 69% for negative IS returns in the test sample, and a total correct classification of 68%, which is far superior to the logistic regression model results. Furthermore, pooled AIC in ANN is 890.33, which is far lower than AIC in the logistic model (2275.6).

Figures 4, **5** depict ANN's model accuracy and model loss in the pooled set.

Figure 6 displays ROC curves for the pooled set, Mainland China, India, and the UAE.

Figure 7 shows the feature importance of pooled and three countries with synoptic weights. **Figure 8** gives the ROC and AUC of ANN models.

Feature Importance in a Pooled Testing Set

Following predictors are positively related to pooled IS in decreasing order of importance. Feature Importance in a Pooled Testing Set is shown in **Table 15**:

- Health predictor HDI is ranked 1 with synaptic weight of 1.96.

TABLE 15 | Feature Importance in Pooled Testing Set.

X5	HDI	1.96
X2	BMA	0.49
X3	Spread	0.36
X1	Neutral	0.33
X6	CHE%GDP	0.29
X13	FDINI-GDP	0.23
X9	Pop-G%	0.19
X12	Interest rate	0.12
X10	Stock $	0.11
X11	Stock TO	0.11
X14	GDP-G%	0.11
X7	Anemia	0.1
X15	INF%	0.05
X16	EC-PE code	0.05
X8	SER-VA%GDP	0.03
X4	USA return	−0.14

TABLE 16 | Feature Importance in China Testing Set.

X1	Neutral	3.46
X2	BMA	2.6
X6	CHE%GDP	0.69
X16	EC-PE code	0.62
X9	Pop-G%	0.56
X3	Spread	0.17
X13	FDINI-GDP	0.15
X14	GDP-G%	0.09
X10	Stock $	−0.07
X11	Stock TO	−0.1
X4	USA return	−0.14
X8	SER–VA%GDP	−0.2
X7	Anemia	−0.52
X12	Int rate	−0.62
X15	INF%	−0.77
X5	HDI	−1

- USA sentiment predictors BMA, Spread, Neutral are ranked 2, 3, 4 with synaptic weights of 0.49, 0.36, and 0.33, respectively.
- Health predictor CHE as % GDP is ranked 5 with synaptic weight of 0.29.
- Macro factor—FDI Net inflow as % GDP is ranked 6 with synaptic weight of 0.23.
- Macro factor—The interest rate is ranked 8 with synaptic weight of 0.12.
- Market fundamentals, such as stock traded in $ terms and stock turnover as a percentage of domestic shares traded, are both ranked 9 with synaptic weight of 0.11, respectively.
- Macro factor GDP % growth is also ranked 9 with synaptic weight of 0.11.
- Health factor anemia (nutritional feature) is ranked 10 with synaptic weight of 0.1.

TABLE 17 | Feature Importance in India Testing Set.

X5	HDI	4.22
X6	CHE%GDP	1.99
X3	Spread	1.4
X7	Anemia	0.36
X14	GDP-G%	0.15
X8	SER-VA%GDP	0.11
X10	Stock $	0.03
X11	Stock TO	−0.02
X13	FDINI-GDP	−0.02
X15	INF%	−0.07
X12	Int rate	−0.09
X16	EC-PE code	−0.19
X4	USA return	−0.48
X1	Neutral	−2.42
X2	BMA	−4.78
X9	Pop–G%	−6.43

TABLE 18 | Feature Importance in the UAE Testing Set.

X1	Neutral	1.73
X6	CHE%GDP	1.12
X16	EC-PE code	0.71
X12	Int rate	0.69
X13	FDINI-GDP	0.44
X10	Stock $	0.24
X15	INF%	0.21
X11	Stock TO	0.19
X8	SER-VA%GDP	0.13
X14	GDP-G%	0.12
X3	Spread	0.08
X9	Pop-G%	0
X4	USA return	−0.01
X2	BMA	−0.71
X7	Anemia	−1.02
X5	HDI	−6.6

- Macro factor inflation is ranked 11 with synaptic weight of 0.05.
- Economic crisis and pandemic events are ranked 11 with synaptic weight of 0.05.
- The services sector as VA% in GDP is ranked 12 with synaptic weight of 0.03. The predictor USA returns (S&P 500) are negatively related to pooled IS and ranked 13 with synaptic weight of −0.14.

Feature Importance in Mainland ChinaTesting Set

The following predictors are positively related to Mainland China IS in decreasing order of importance. Feature Importance in China Testing Set is shown in **Table 16**:

- USA sentiment predictors Neutral BMA are ranked 1 and 2 with synaptic weights of 3.46 and 2.6, respectively.

TABLE 19 | Confusion (classification) matrix.

		Predicted		T	
		1	0		
Country/territory 1 = Mainland China					
Actual	1	82	3	85	0.96
	0	70	19	89	0.21
	T	152	22	174	0.58
Country/territory 2 = India					
Actual	1	70	16	86	0.81
	0	26	56	82	0.68
	T	96	72	168	0.75
Country/territory 3 = UAE					
Actual	1	4	51	55	0.07
	0	3	130	133	0.98
	T	7	181	188	0.71

- Health predictor CHE as % GDP is ranked 3 with synaptic weight of 0.69.
- Economic crisis and pandemic events are ranked 4 with synaptic weight of 0.62.
- USA sentiment predictor spread is ranked 6 with synaptic weight of 0.17.
- Macro factor - FDI net inflow as % GDP is ranked 7 with synaptic weight of 0.15.
- Macro factor GDP % growth is ranked 8 with synaptic weight of 0.09.

The following predictors are negatively related to Mainland China IS in decreasing order of importance:

- Market fundamentals, such as stock traded in $ terms and stock turnover as percentage of domestic shares traded, are ranked 9 and 10 with synaptic weight of −0.07 and −0.1 respectively.
- USA (S&P 500) return is ranked 11 with synaptic weight of −0.14.
- The services sector as VA% in GDP is ranked 12 with synaptic weight of −0.2.
- Health factor anemia (nutritional feature) is ranked 13 with synaptic weight of −0.52.
- Macro factor - interest rate and inflation are ranked 14 and 15 with synaptic weight of −0.62 and −0.77 respectively.
- Health predictor HDI is ranked 16 with synaptic weight of −1.

Feature Importance in India Testing Set

The following predictors are positively related to Indian IS in decreasing order of importance. Feature Importance in India Testing Set is shown in **Table 17**:

- Health predictors HDI, CHE% GDP are ranked 1 and 2 with synaptic weights of 4.22 and 1.99, respectively.
- USA sentiment predictor spread is ranked 3 with synaptic weight of 1.4.

- Health predictor anemia (nutrition feature) is ranked 4 with synaptic weight of 0.36.
- Macro factor - GDP growth % is ranked 5 with synaptic weight of 0.15.
- The services sector as VA% in GDP is ranked 6 with synaptic weight of 0.11.
- Market fundamental such as stock traded in $ terms is ranked 7 with synaptic weight of 0.03.

Following predictors are negatively related to Mainland China IS in decreasing order of importance:

- Market fundamental stock turnover as a percentage of domestic shares traded is ranked 8 with synaptic weight of −0.02.
- Macro factors FDI NI as % GDP, inflation, and interest rate are ranked 9, 10, 11 with synaptic weight of −0.02, −0.07, and −0.09, respectively.
- Economic crisis and pandemic events are ranked 12 with synaptic weight of −0.19.
- USA return (S&P 500) is ranked 13 with synaptic weight of −0.48.
- USA sentiment predictors Neutral and BMA are ranked 14 and 15 with synaptic weights of −2.42 and −4.78, respectively.

Feature Importance in the UAE Testing Set

The following predictors are positively related to the UAE IS in decreasing order of importance. Feature Importance in the UAE Testing Set is shown in **Table 18**:

- USA sentiment predictor neutral is ranked 1 with synaptic weight of 1.73.
- Health predictor CHE% GDP is ranked 2 with synaptic weight of 1.12.
- Economic crisis and pandemic events are ranked 3 with synaptic weight of 0.71.
- Macro factors interest rate% and FDI NI as % GDP are ranked 4 and 5 with synaptic weights of 0.69 and 0.44, respectively.
- Market fundamental stock traded in $ terms is ranked 6 with synaptic weight of 0.24.
- Macro factors inflation % is ranked 7 with synaptic weight of 0.21.
- Market fundamental stock turnover as percentage of domestic shares traded is ranked 8 with synaptic weight of 0.19.
- The services sector as VA% in GDP is ranked 9 with synaptic weight of 0.13.
- Macro factor - GDP growth % is ranked 10 with synaptic weight of 0.12.
- USA sentiment predictor spread is ranked 11 with synaptic weight of 0.08.
- Health predictor anemia (nutrition feature) is ranked 4 with synaptic weight of 0.36.

The following predictors are negatively related with the UAE IS in decreasing order of importance:

- USA return (S&P 500) is ranked 13 with synaptic weight of −0.01.

TABLE 20 | A summary of diagnostic results from ANN and logistic models.

Diagnostics >	N*	Accuracy			F-1 score			AIC			AUC			Total correct classification % (confusion matrix)		
Metrics >		L	ANN	T values	L	ANN	T values	L	ANN	T values	L	ANN	T values	L	ANN	T values
Pooled set	1,326	0.67	0.68	−2.459	0.64	0.63	2.459	2,275.6	890.33	340,593	0.6132	0.73	−28.717	61.32	68	−1,642.4
Mainland China	436	0.63	0.6	6.168	0.63	0.6	6.168	821.19	150.33	137,920	0.49	0.62	−26.726	49.81	58	−1,683.8
India	420	0.7	0.67	3.184	0.66	0.69	−3.184	715.8	124.22	62,777	0.6871	0.73	−4.552	70.21	75	−508.3
UAE	470	0.74	0.77	−4.689	0.65	0.69	−6.252	746.88	175.44	89,311	0.498	0.58	−12.816	74.02	71	472.0

*The test sample is 50% random of the whole data set; Index L, logistic; ANN, artificial neural network; T-value, actual values lying outside the critical values at α < 0.005.

- USA sentiment predictor BMA is ranked 14 with synaptic weight of 0.71.
- Health predictors anemia (nutrition feature) and HDI are ranked 15 and 16 with synaptic weight of −1.02 and −6.6, respectively.

Classification (Confusion) Matrix in a Testing Set

From **Table 19** in the test sample:

- in Mainland China (Panel-A), the classification percentage is 96% for positive IS returns, 21% for negative IS returns, and a total correct classification of 58%.
- in India (Panel-B), the classification percentage is 81% for positive IS returns, 68% for negative IS returns, and a total correct classification of 75%.
- in the UAE (Panel-C), the classification percentage is 7% for positive IS returns, 98% for negative IS returns, and a total correct classification of 71%.

Table 20 summarizes the diagnostic results to show the superiority of ANN over the logistic model in predicting IS. All *t*-values are highly statistically significant. In the pooled set, AIC is lower, AUC is higher, accuracy is higher, the F-1 score is marginally lower, and correct classification % is higher in ANN than in logistic specification. This further validates that the ANN model is superior to Logistic Model for IS predictability in these emerging markets.

Model Validation

Artificial neural networks (ANN) can be built with a great combination of hidden layers, optimizers, activation functions, etc., based on the application's needs. The dataset fed as an input to the ANN is often split into three categories using python packages from scikit-learn. These categories are:

1. Training dataset: This is the dataset from which the model will learn the essential features by performing repeated runs on the dataset. Quintessential features are identified and learned from this dataset.
2. Validation dataset: This is the segment of the dataset, which is used to tune the neural network hyper-parameters to adjust the learning by the model over time. The dataset chosen for

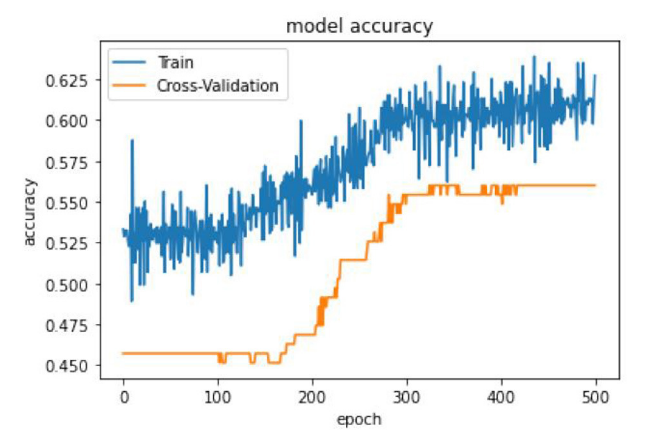


FIGURE 10 | ANN model accuracy-Main Land China.

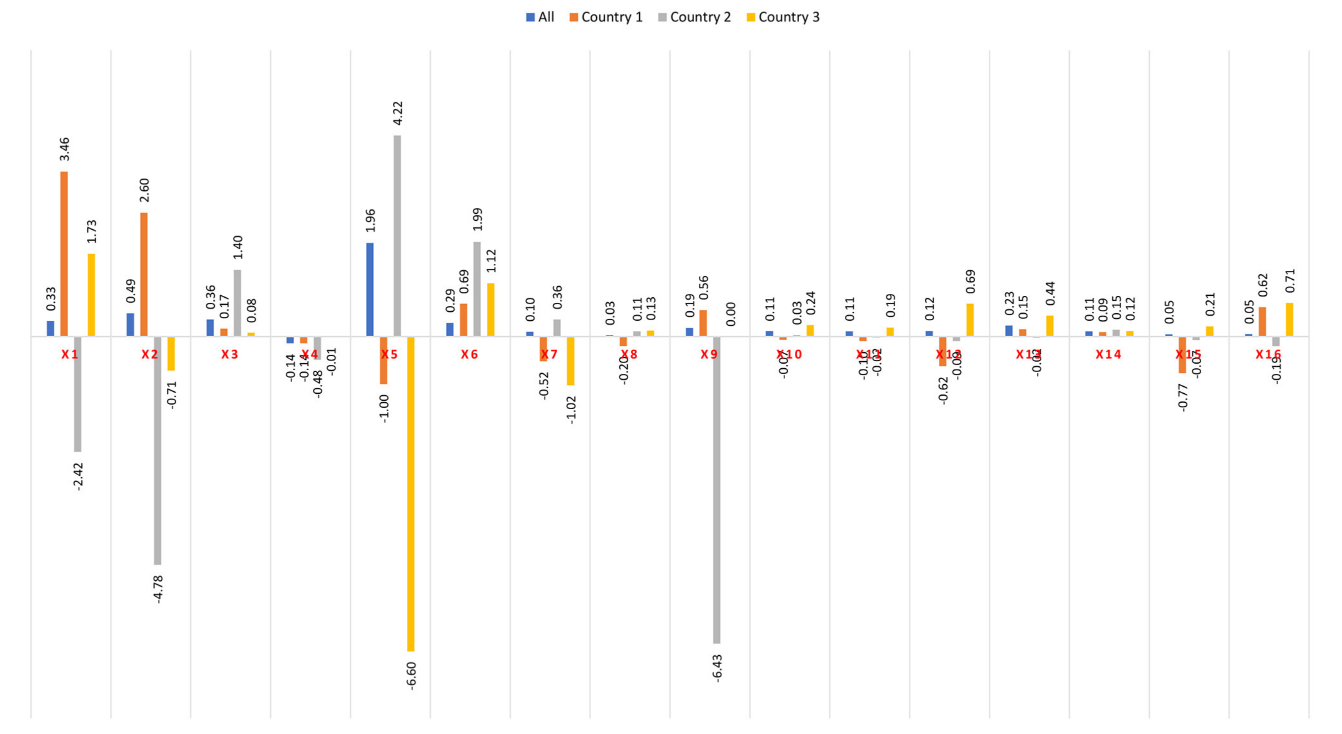


FIGURE 9 | Feature importance of predictors in a pooled set and in each country/territory (1 = Mainland China, 2 = India, and 3 = UAE).

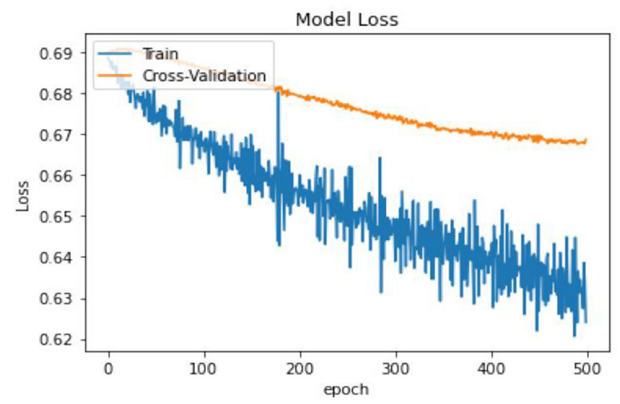


FIGURE 11 | ANN model loss-Main Land China.

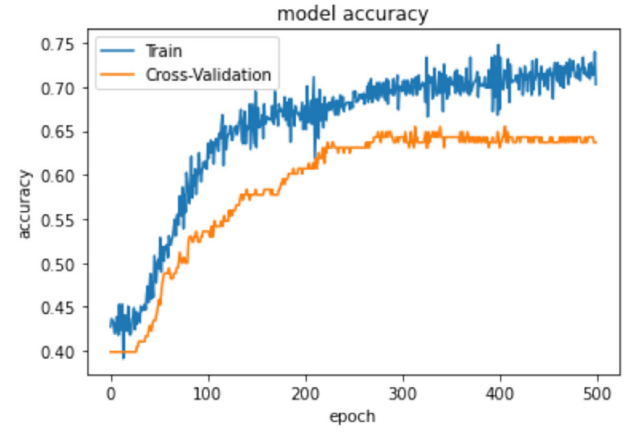


FIGURE 12 | ANN model accuracy-India.

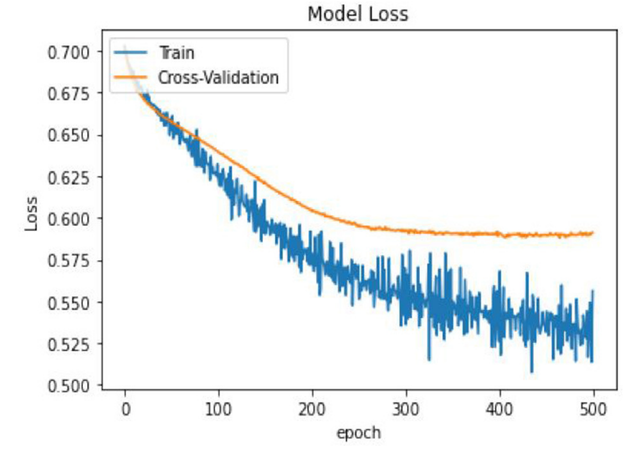


FIGURE 13 | ANN model loss-India.

this validation should not be used either as a training or testing dataset.

3. Testing dataset: This is the dataset independent of the above two datasets; the model that was trained earlier is fed with this dataset, and a measure of performance is recorded.

We have used 50% of the dataset for training in our model, and the remaining 50% is split between validation and testing datasets, respectively. The model's performance on a testing dataset is what the model's actual performance is and can be changed by turning the neural network hyper-parameters.

ANN AIC, AUC, Confusion Matrix, Accuracy, F-1 Scores

We applied the pooled 3 layers in the ANN architecture using the SGD optimization criterion to three emerging markets to see how they performed in each country/territory in terms of model performance in the training set, evaluation/training set, and validation set.

- Mainland China ANN (AIC = 150.33) model performance; training accuracy: 0.61; evaluation accuracy: 0.56; and validation accuracy: 0.58.
- India ANN (AIC = 124.22) model performance: training accuracy: 0.72; evaluation accuracy: 0.64; and validation accuracy: 0.75.
- UAE ANN (AIC = 175.44) model performance: training accuracy: 0.75; evaluation accuracy: 0.75; and validation accuracy: 0.6.

Figures 9–15 depict model accuracy and model loss for each country/territory.

Furthermore, health predictor current health expenditure as a percentage in GDP (CHE% GDP), USA IS predictor spread, and macro factor GDP-G% are the common predictors across the pooled, Mainland China, India, and the UAE testing set that positively impacts the emerging markets' IS behavior. USA (S&P 500) return is the only common predictor across the pooled, Mainland China, India, and the UAE testing set that negatively impacts the emerging markets' IS behavior. The magnitude of impact, however, varies across the countries.

The preceding results answer our second research objective in that emerging market investors in each of the three countries have varied IS behaviors for deriving higher positive returns in the backdrop of USA IS.

Regarding the second research objective, in general, macroeconomic factors had a less diverse impact on investors' return expectations in all the 3 countries. This implies that different policy actions need to be taken by respective country/territory governments to stimulate FDI inflow and GDP growth and interest rate management while controlling inflation to ensure dynamic and vibrant financial markets for attracting both domestic and foreign investors for investments in various health and services sector promotion initiatives discussed in detail in section Healthcare Trends Post COVID-19 of the manuscript to ensure UHC and achieve SDG 3 and 8 by 2030.

About the fourth research objective, the charts on predictors' feature importance for pooled countries and individual countries reveal no contemporary relation among the predictors across the three countries, but the magnitude of impact on IS returns is not uniform.

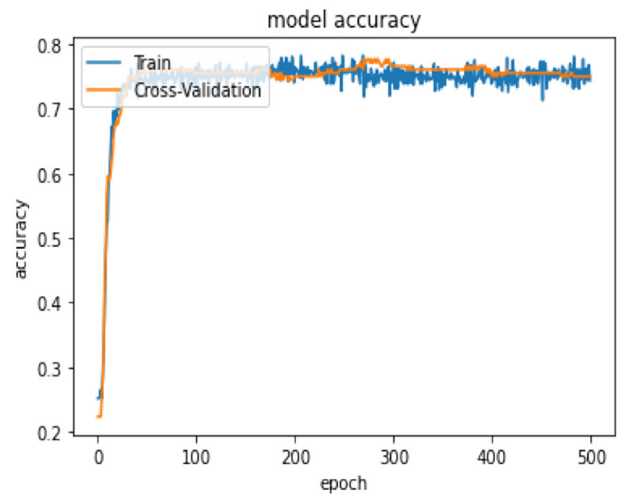


FIGURE 14 | ANN model accuracy-the UAE.

CONCLUSION AND LIMITATIONS

This paper presents a data model to assess investors' behavior to attract more investments that meet the United Nation's Sustainable Development Goals 3 (health and wellbeing) and 8 (growth and economic development). The proposed artificial neural network (ANN) model analyzes the investor sentiments (IS) to capture the investors' behavior proxied by equity returns. The performance and generalization of the model have been experimentally demonstrated against three fast-emerging economies, i.e., Mainland China, India, and the UAE. Specific research objectives to attract investments in Health Sector and Growth in emerging markets, *viz.*, India, Mainland China, and the UAE, are:

1. What are specific healthcare sector opportunities available in the three markets?
2. Are the USA-IS key IS predictors in the three economies?
3. How important are macroeconomic and sociocultural factors in predicting IS in these markets?

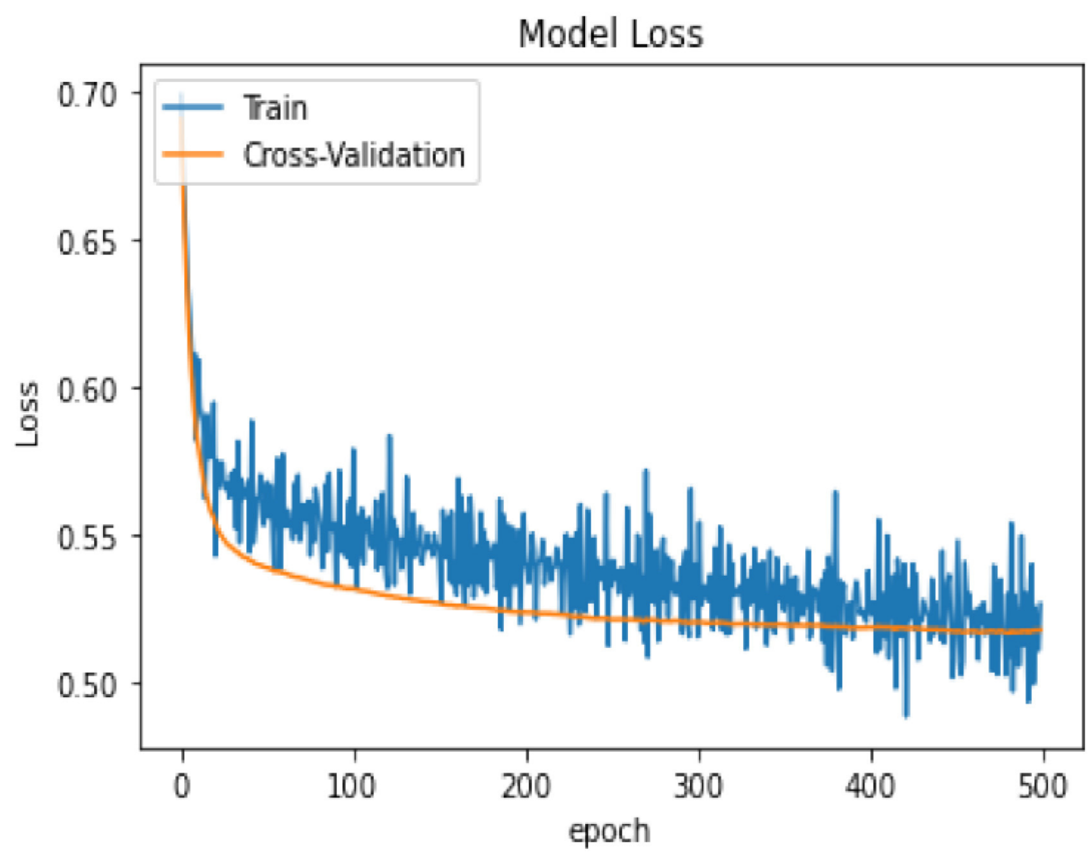


FIGURE 15 | ANN model loss-the UAE.

4. How important are economic crises and pandemic events in predicting IS in these markets?
5. Is there contemporaneous relation in predicting IS across the three countries in terms of USA-IS? And, if yes, is the magnitude of the impact of USA-IS uniform across the three countries' IS?

Logistic regression (traditional model) and ANN model are applied to capture behavioral elements in the investors' decision-making in these emerging economies, using weekly historical data from January 1, 2003 to December 31, 2020. Health predictor - current health expenditure as percentage in GDP (CHE% GDP), USA IS predictor - spread, and macro-factor GDP-annual growth % are the common predictors across the Pooled, Mainland China, India, and the UAE testing set that positively impacted the emerging markets' IS behavior. USA (S&P 500) return is the only common predictor across the Pooled, Mainland China, India, and the UAE testing set negatively impacted the emerging markets' IS behavior. The magnitude of impact, however, varies across the countries.

The ANN results discussed in section Model Results answer our research objectives adequately. In addition, emerging market investors in each of the three countries have varied IS behaviors for deriving higher positive returns in the backdrop of USA IS, which answers the second objective.

Regarding the third research objective, in general, macroeconomic and sociocultural factors had a less diverse impact on investors' return expectations in all the 3 countries. This implies that different policy actions need to be taken by respective country/territory governments to stimulate FDI inflow and GDP growth and interest rate management while controlling inflation to ensure dynamic and vibrant financial markets for attracting both domestic and foreign investors for investments in various health and services sector promotion initiatives discussed in detail in section Healthcare Trends Post COVID-19 of the manuscript to ensure UHC and achieve SDG 3 and 8 by 2030.

About the fourth objective, the economic crisis and pandemic events had a diverse impact on each of the three emerging markets. This motivates policy formulation to exploit opportunities (Research Objective 1) identified in section Healthcare Trends Post COVID-19 of this paper to minimize the detrimental effects of these crises and pandemic events not only on their citizens in general but also on investors in particular by infusing confidence through their proactive citizen investor-centric policies for sustainable development.

About the fifth research objective, the ANN (**Figure 7**) on predictors' feature importance for pooled countries and individual countries reveals that there is no contemporaneous relation among the predictors across the three countries, but the magnitude of impact on IS returns is not uniform.

Summary of Findings

- The empirical findings confirmed the superiority of the ANN framework over the traditional logistic model in capturing the cognitive behavior of investors.
- Health predictor - current health expenditure as a percentage of GDP (CHE% GDP),
- USA IS predictor - spread, and
- Macro-factor GDP - annual growth % are the common predictors across the 3 economies that positively impacted the emerging markets' IS behavior.
- USA (S&P 500) return is the only common predictor across the three economies that negatively impacted the emerging markets' IS behavior.

However, the magnitude of both positive and negative impacts varies across the countries, signifying unique, diverse socioeconomic, cultural, and market features in each of the 3 economies.

The study results have four key implications: Firstly, US market sentiments are an essential factor influencing stock markets in these countries. Secondly, there is a need for developing a robust sentiment proxy on similar lines to the USA in the three countries. Thirdly, investment opportunities in the healthcare sector in these economies have been identified for potential investments by the investors. Fourthly, this study is the first study to investigate investors' sentiments in these three fast-emerging economies to attract investments in the health sector and growth in the backdrop of UN's 2030 SDG 3 and SDG 8 targets to be achieved by these economies.

Study Limitations and Future Directions

Although the conceptual framework excluded public news tracked through social media due to the non-availability of consistent data, with the digitalization of each activity in the wake of technological advances and AI analytics, we feel that there is a need to include these features in IS modeling to improve the performance of the sentimental model developed in this paper. Future studies could also explore alternative NNs, such as Convolutional Neural Network, Radial Basis Functional Neural Network, Recurrent Neural Network, LSTM—long short-term memory, and Sequence to Sequence Models as alternatives to ANN to evaluate model performance.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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ICT Enabled Disease Diagnosis, Treatment and Management—A Holistic Cost-Effective Approach Through Data Management and Analysis in UAE and India

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This concept paper addresses specific challenges identified in the UN 2030 Agenda Sustainable Development Goals (SDG) as well as the National Health Policy of India (NHP-India) and the Ministry of Health Policy of UAE (MHP-UAE). This policy calls for a digital health technology ecosystem. SDG Goal 1 and its related objectives are conceptualized which serves as the foundation for Virtual Consultations, Tele-pharmacy, Virtual Storage, and Virtual Community (VCom). SDG Goals 2 and 3 are conceptualized as Data Management & Analytical (DMA) Architecture. Individual researchers and health care professionals in India and the UAE can use DMA to uncover and harness PHC and POC data into practical insights. In addition, the DMA would provide a set of core tools for cross-network initiatives, allowing researchers and other users to compare their data with DMA data. In rural, urban, and remote populations of the UAE and India, the concept augments the PHC system with ICT-based interventions. The ICT-based interventions may improve patient health outcomes. The open and flexible design allows users to access various digital materials. Extendable data/metadata format, scalable architecture for petabyte-scale federated discovery. The modular DMA is designed using existing technology and resources. Public health functions include population health assessment, policy development, and monitoring policy implementation. PHC and POC periodically conduct syndromic surveillance to identify population risk patterns. In addition, the PHC and POC deploy medical and non-medical preventive measures to prevent disease outbreaks. To assess the impact of social and economic factors on health, epidemiologists must first understand diseases. Improved health due to compliance with holistic disease treatment plans and access to scientific health information.

Keywords: SDG-3, SDG-8, virtual health clinics (VHC), Primary health centers (PHC), point of care (POC), out of pocket expenses, SDG-9

INTRODUCTION

Technological advancements/new discoveries/innovations are transforming care delivery methods and enhancing patient care experiences. It is required to develop evidence on how the innovations/advancements in healthcare can be made accessible by all in a cost-effective manner. It is also a need of the hour to deploy such technological advancements in the nearest point of care (POC) accessible by every common man. PoC is considered any location where patient care is provided (e.g., clinic, the bedside, home, or ambulance). Therefore, this conceptual paper focuses on using Patient-Centred Digital Healthcare Technologies (PC-DHT) to help provide the best health care to the local population in rural and semi-urban areas in India and remote places in UAE by setting up virtual health clinics to connect patients to the specialist doctors. After a virtual consultation and the necessary testing, the disease diagnosis is recorded in electronic health records (EHR). Once the diagnosis is complete, PC-DHT can help to draw up a detailed, holistic treatment plan. Using Web, and Mobile apps, the patient will be provided holistic treatment plans with details on the diagnosis, treatment schedule, prescription, diet, exercise etc. The data thus generated from multiple POC are made available to diverse domain researchers in the consortium of institutions through a secure and effective data management and analysis (DMA) architecture. This DMA architecture would help generate more fact-based information that aids in adaptive learning for cost-effective holistic diagnosis, treatment, and management remotely.

BACKGROUND

The current practices in healthcare delivery are blended with the help of new technological innovations. This concept paper emphasizes the design and development of the platform, which fully utilizes state-of-the-art technological advancements to improve healthcare delivery. This manuscript details the methodology for exchanging health information data and facilitating smart gadgets to capture real-time data and the methods to help the current healthcare industry. Further, this concept paper proposes an electronic approach to good health, responds to the specific challenges identified in the United Nations (UN) 2030 Agenda Sustainable Development Goals (SDG) as well as the National Health Policy of India (NHP-India) and the Ministry of Health Policy of UAE (MHP-UAE).

The uniqueness of the concept lies in the fact that the conceptual framework provides patients, including their data, access to specialist doctors from around the globe *via* the VHC;

BOX 1 | Index of Acronyms.

Index	Acronym Details	Index	Acronym Details
ABS	Ayushman Bharat Scheme	NHIA	National Health Information Architecture
ADHA	Abu Dhabi Health Authority	NHIN	National Health Information Network
AI	Artificial Intelligence	NHP	National Health Policy
API	Application Programming Interface	NHP-India	National Health Policy of India
AWS	Amazon Web Services	NITI	National Institution for Transforming India
CC	Coordination Center	NLP	Natural Language Processing
CD	Communicable Diseases	NMIT	Nitte Meenakshi Institute of Technology
CDSS	Clinical Decision Support Systems	O	Objectives
DHA	Dubai health Authority	OSI	Open Systems Interconnection
DMA	Data Management & Analysis	ODSP	Open Data Solution Provider
EHR	Electronic Health Records	OoPE	Out of Pocket expenses
EIPM	Evidence-informed policy making	ORI	Offices of Research & Innovation
G	Goals	PC-DHT	Patient-Centered Digital Healthcare Technologies
GIS	Geographical Information Systems	PDA	Personal Digital Assistants
GOI	Government of India	PHC	Primary Health Centers
GPS	Geographical Position Systems	POC	Point of Care
GUI	Globally Unique Identifier	RMCH	Ramaiah Medical College & Hospitals -Bangalore-India
HP	Health professionals	SDG	Sustainable Development Goals
ICMR	Indian Council of Medical Research - New Delhi-India	SOP	Standard Operating Procedures
ICT	Information, Communication & Technology	SSP	Software Sharing Plan
IoT	Internet of Things	TP	Tele-pharmacy
IT	Information Technology	UAE	United Arab Emirates
MBRSG	Mohammed Bin Rashid School of Government -Dubai-UAE	UD	University of Dubai (UAE)
MDDS	Metadata and Data Standards	UN	United Nations
mH	Mobile Health	UN	United Nations
MHP-UAE	Ministry of Health Policy of UAE	VC	Virtual consultations
ML	Machine Learning	VCom	Virtual community
NCD	Non-communicable diseases	VHC	Virtual Health Clinics
NDHM	National Digital Health Mission	VNR	Voluntary National Review
NET	Nitte Education Trust	VPN	Virtual private network
NGO	Non-Government Organizations	VSS	Virtual storage space

Improved health due to compliance to holistic disease treatment plans, and access to scientific health information; and Reduction in OoPE to patients.

Research Problem

Today's healthcare systems in India and UAE need significant enhancement in their operation. This enhancement needs to be in the dimension of using ICT facilities in healthcare. ICT-enabled PHC will improve patient health outcomes in rural, urban, and remote populations of the UAE and India. Further, it allows patients/healthcare practitioners to access various digital materials. The focus of this concept paper is to propose a modular and scalable DMA designed based on current innovations in ICT. The creation of DMA using current advancements in ICT will facilitate Health Informatics, TeleHealth, Tele Medicine, E-Learning platforms, and Electronic Commerce.

Problem Description

Design and development of the platform for exchanging health information data and facilitating smart gadgets to capture real-time data are the critical aspect of the National Health Information Architecture (NHIA). The critical aspects of NHIA are in line with the Pan American Health Organization's (PAHO, 2011) Strategy and plan of action on eHealth (Scott, 2009). The goals of NHIA, PAHO, and strategy and plan of action on eHealth provide the following four critical components for facilitating cost-effective healthcare for all.

- Health Informatics: It works to combine information networks related to healthcare data. Secondly, it targets consolidating the electronic health records and related services for assimilating and analyzing the healthcare records.
- Telehealth and Telemedicine: It facilitates interaction (direct or virtual) with remote health care professionals/providers for patients with limited mobility and ill health. (National Academy of Sciences, 2015).
- E-Learning: It promotes the usage of ICTs facilities to promote education and learning opportunities to the people involved/delivering healthcare-related services. E-Learning will extend the knowledge of healthcare workers, and they can access the content at any time from anywhere. Here one can learn at their own pace and repeat the lessons. E-learning is a suitable means to educate the masses and citizens.
- Electronic commerce: Focuses on business areas of healthcare-related activities. For example: controlling services related to patients through hospital information systems (cost of the treatment, administrative information etc.).

Objectives of the Study

To address these needs, the specific Goals and Objectives of this concept paper are:

Goal.1

To improve patient experiences and healthcare service delivery at the point of care, use new, patient-centered, clinician- and patient-oriented digital healthcare technology. This goal is accomplished by the following set of Objectives (O):

O.1.1 Setup Virtual Health Clinics (VHC) in Urban and Rural settings in India and remote locations in UAE over 4–5 years. VHC enables patients to consult with specialist doctors remotely to help patients get disease diagnoses and follow-ups.

O.1.2 Deploy web and mobile apps to provide health information and implement holistic disease treatment plans for patients. In addition to medication, there would be actionable instructions on diet, supplements, exercise, lifestyle modifications, and a comprehensive treatment schedule and reminders.

O.1.3 Integrate all stakeholders like doctors, nurses, and family members in designing and implementing the holistic disease treatment plans for patients using ICT.

O.1.4 Make available the electronic health record (EHR) data for disease registries, further research, and analysis while preserving the patient's privacy.

Goal 2

Examine how patient-centered digital healthcare technology [such as wearables, sensors, and m-Health (mH) solutions] affect patient outcomes, experiences, and the delivery of healthcare services at the point of care. The following Objectives (O) are used to achieve this goal:

O.2.1 Deploy innovative & cost-effective ICT for storing and disseminating Health Information. Integrate data from disparate sources and formats into longitudinal, standards-compliant EHR. These applications are expected to assess and evaluate the technology implementation's impact on practice workflow and quality of care.

Goal 3

Use advanced analytics to improve quality at the point of care. This goal is accomplished by the following set of objectives (O):

O.3.1 Test innovative digital clinical decision-making tools (such as AI and ML) that incorporate patient-generated data and patient-reported outcomes at the point of care.

O.3.2 Examine digital point-of-care systems that integrate natural language processing (NLP) with a decision support tool to transform unstructured clinical data into knowledge and make that information easier to use.

Expected Impact and Outcomes

For the **patient**, the expected outcome from the concept is:

a. *Access to specialist doctors from around the globe via the VHC*
Rural patients are hindered by the lack of access to specialist doctors. Therefore, disease diagnosis may be delayed, and proper treatment may be difficult. The ICT-enabled virtual clinic would help patients' access specialist doctors.

b. *Improved health due to compliance to holistic disease treatment plans and access to scientific health information.*
Treatment of diseases encompasses taking the prescribed medication, adhering to the diet plan, and exercising regularly. ICT would help patients adhere to the treatment schedule and plan. The use of activity trackers would help improve the physical activity levels in patients. This would directly impact the recovery and the general health of patients. Providing

adequate health information would enable patients to make better health care decisions.

c. *Reduction in OoPE*
Access to the VHC would reduce the travel expenses for disease treatment. In addition, e-prescription and e-procurement can help lower the cost of medication.

For doctors and health care workers, the expected outcome is: To have effective and efficient access to patients, including their data, beyond their geographical boundaries. Access to laboratory reports, e-prescriptions, and feedback on patient compliance is provided. The comprehensive EHR would enable doctors to make better health care decisions. The EHR would help the health care workers assess the patient's adherence to the treatment plan. The ICT would help the health care worker disseminate scientific information about diseases, their treatment, and management.

For public health policymakers and medical research, the expected outcomes are as under:

Comprehensive EHR would be beneficial in forming disease registries. The consolidated disease-specific information would spur AI/ML-based studies and provide insight into disease treatment and management by continually managing all types of data from all stakeholders, analyzing them scientifically, generating new facts, exploring patterns, and valuable for practicing healthcare professionals and patients through an adaptive learning feedback loop. This would enable the policymakers to make evidence-based health policies. The concept would have intended impact and outcomes when jointly designed and developed with different stakeholders, including the Government, PHC, Academia, and policy actors.

For the local community, the expected outcome is: Improved patients' health in the community would result in a marked improvement in the local population's health. The involvement of healthcare workers and even the family would ensure that the patient is more likely to comply with the treatment plan. The setup of VCom spurs community engagement and would improve the community's socio-economic status.

The concept would have maximum impact when the concept's goals and objectives, experiment group, and methodology are jointly discussed, designed, and developed with the local population. Adaptive learning through constant feedback, structured interviews, and focus group discussions would help derive maximum impact of the concept during implementation. Performance metrics would be designed in consultation with the local community to assess patient compliance to a comprehensive treatment plan. A dashboard with metrics to track the concept at the population level would be set up at the VHC to maximize the impact.

The Rationale for Choosing UAE and India

According to the United Nations Development Programs (UNDP's) Human Development Index (HDI, 2020) report, the UAE is well-developed, with an HDI rating of 31, whereas India is deemed poor, with an HDI score of 131. Comparing and contrasting excellent practices in these two extreme situations allows for a more comprehensive understanding and application of the recommended principles.

Uniqueness and Significance

Urban, Rural, and Remote Health Centers are the backbones of healthcare services in India and the UAE. The primary functions of public health include health assessment of the population, policy development, and assurance that the policies have been implemented appropriately. PHC periodically performs syndromic surveillance and attempts to identify the risk patterns in the population. The public health organization deploys can use PHC to promote medical/non-medical preventive methods to prevent disease outbreaks.

Administration of antiviral medicines, vaccination drives, medical tests etc., are some examples of clinical preventive measures. Clinical preventive measures help promote good health by preventing the spread of diseases. On the other hand, establishing quarantine facilities, providing easy access to clean drinking water, creating mass awareness of health-related information etc., are part of non-medical mitigation strategies. Epidemiologists need to understand diseases, perform statistical analysis of data, and study social and economic conditions to assess their impact on health. This is the first rationale for this proposed concept.

The second rationale stems from Voluntary National Review (VNR) 2020 report on India's and UAE's performance regarding the SDG. SDG has finetuned development policies, government priorities, businesses and citizen responsibility, and metrics for quantifying self-growth worldwide. India and UAE have implemented the SDG 2030 agenda and associated their growth priorities with the universal goal of all other countries. For the health care sector, the report identifies three challenges in India:

a. Affordability and the cost of healthcare: Healthcare services offered by the public sector, while cost-effective, they are not the first choice for patients, as they are perceived as unreliable and of poor quality. The private sector is dominant in healthcare. However, there is a disparity in quality and cost of services among private health care providers;
b. Health workforce density: Even though the number of midwives, nurses, and physicians per 10,000 people increased by 1.7%, it is astonishing to note that India has the lowest density of health care professionals when compared to other countries worldwide
c. Lack of Health Awareness: Major gaps were identified in awareness about health care, particularly in parts like infant and adolescent health and sexual and reproductive healthcare. There is no awareness about diet and nutrition necessities, including lifestyle, mental health, and geriatric morbidity. For UAE specifically, the challenge is as mentioned under (c) above, while UAE has minimized the gaps under challenges a and b above. This concept addresses these challenges since Good Health among the population would further spur the economic growth of Indian and UAE citizens.

The third rationale is that SDG- 3 discusses India's and UAE's performance in the health care sector in terms of good health and wellbeing. India's and UAE's focus has been universally promoting preventive healthcare, empowering primary healthcare affordability, and improving the medical infrastructure. In India, the Pradhan Mantri Jan Aushadhi

Pariyojana has been actively being implemented for a few years. Under Pradhan Mantri Jan Aushadhi Pariyojana, the patients are given quality medicines at effective prices. It has played an active role in decreasing patients' out-of-pocket expenses (OoPE). Additionally, the free drugs service initiative has provided the availability and accessibility of diagnostic services at the district and sub-district levels across the country—all these measures have significantly brought down OoPE.

The fourth rationale is that India and UAE are among the initial few countries to establish exact goals and pointers to reduce a load of non-communicable diseases (NCD) mortality by 25% by 2025. The growth of the National Programme for the Prevention and Control of Cancer, Diabetes, Cardiovascular Diseases, and Stroke (NPCDCS) in both nations has bolstered India's and the UAE's response to NCD. The Mental Healthcare Act was passed in 2017, and it took an entitlement approach to provide mental healthcare and services and raising awareness about mental health.

The fifth rationale is that moving toward universal health coverage, accessible, affordable, and quality health care has been institutionalized through mHealth/mH remote consultation services, and the setting up of health and wellness centers in rural, urban and remote areas has been listed as proposed health policy reforms in both UAE and India. The setting up of integrated public health labs in all districts & block level labs has also been discussed and, once implemented, would result in OoPE for the patients.

The application of ICT to COVID-19 in India and UAE is a classic case of how both countries have effectively used ICT to treat and manage the disease by exploiting the technology. The Arogya Setu App is a COVID-19 tracking mobile application produced by the Government of India. Alhosn is a comparable application in the UAE. Using cutting-edge Bluetooth technology and AI-based algorithms, both applications allow users know the danger of Corona Virus grounded on their contacts with others. The applications supplement health programs in the UAE and India to reduce COVID-19 hazards and exchange best practices. They are the fastest-growing mobile application globally, with over 100 million downloads on the major application distribution networks weeks after the launch. It currently provides 100 million customers with online medical consultations (phone and video), home lab tests, and e-pharmacy.

Another important health-related policy document is the National Health Policy (NHP), 2017. Effective use of ICT plays a vital role in achieving the goals of the NHP. For instance, the NHP 2017 recognizes the importance of digitization and wants to ensure a district-level electronic database of health information. The NHP 2017 acknowledges the key usefulness of ICT in healthcare delivery (eHealth, IoT, mHealth, and wearable electronic smart devices with customized pre-installed software suite). Similarly, NDHM works on the lines of penetrating the usage of digital health-related technologies to efficiently deliver healthcare innovations to the last person of society. Identifying the usefulness of EHR digitization, the NHP stresses the implementation of EHR electronic databases at the district level. This will further strengthen healthcare survivance and drive healthcare innovation at the level of establishing the public database/registries related to diseases of public health. It will also speed up the development of a federated learning environment for healthcare information systems, health Information Exchanges, and the National Health Information Network (NHIN) by 2025.

SDG-8 focuses on Decent Work and Economic Growth. This means that a healthy population equals a more productive workforce. Human capital investment may significantly boost a country's competitiveness. Vaccinated, healthy youngsters develop into productive workers who contribute significantly to the economy. Furthermore, healthy children free up their parents' time, allowing them to work. In Gavi-supported countries, every US dollar invested in immunization yields an additional US dollar 54 in broader social benefits such as individuals living longer and better lives (https://www.gavi.org/our-alliance/global-health-development/sustainable-development-goals).

SDG-9 emphasizes the need for Innovation, ICT, and IT Infrastructure for health care needs. The interactions between health care workers and patients would be recorded in blockchain-based systems to integrate the patient's health information into a comprehensive longitudinal record. Holistic treatment plans would be customized for the patient by health care workers. Information about the treatment plan and general information about disease management would be shared through Web and mobile apps. Cost-effective activity trackers would be provided for patients to monitor their physical activity and sleep cycles. Electronic dashboards would be set up in the PHC to assess the effect of the ICT Healthcare concept on individual patients and the local population. Involving policymakers in the early phase of research enhances the utilization of research findings in the design and delivery of national programs in both the UAE and India. The concept team is experienced in the required technical know-how.

STUDY DESIGN AND METHODS

This section briefs the Design/Conceptual Framework for Goal 1 (O.1.1–O.1.4), and Goals 2 & 3 and their related objectives.

Design/Conceptual Framework for Goal 1 and Objectives O.1.1–O.1.4

How the care is given in POC can be transformed with the help of evidence-based, technology-driven solutions. These solutions may boost efficiency, minimize mistakes, improve safety, and expand patient participation and shared decision-making possibilities.

Usage of Patient-centered digital healthcare technologies (PC-DHT), Artificial Intelligence (AI) driven software/hardware, and Clinical Decision Support Systems (CDSSs) are extensively being deployed primarily for efficient and effective healthcare delivery, effective patient engagement, quality care, and to mitigating the risks of the healthcare process. For example, AI-based diagnostic treatments are currently delivered using Health AI apps (Yu et al., 2018). Many people use health-related applications installed on intelligent gadgets during day-to-day life, consisting of sensors and Patent Centered Digital Healthcare Technologies (PC-DHT), which are extensively used to deliver effective treatment outcomes (Kabelac et al., 2019).

The goal of PC-DHT is to collect the data from patients and supply the collected data to healthcare systems that can be used for informed decisions, supporting the collaborative decision-making process, and it enhances self-care quality. Healthcare professionals primarily use clinical Decision support systems to connect the healthcare knowledge at their fingertips (Baig et al., 2017). It also aids in the understanding of trends in the healthcare data and how these innovations affect the outcomes related to healthcare, delivery, and quality, which will be ultimately linked to patient experiences- this area can be explored further. Research into the utilization of novel PC-DHT systems to enhance services at the point of care correlates with the United Nations' SDG-3 goal, maximizing the value received from healthcare spending while providing 360-degree care.

With ICT and other technological advancements, the issues associated with old-aged populations (such as chronic illnesses) can be mitigated effectively. For example, people can use wearable or smart gadgets to track blood glucose, heart rate, and temperature in old age. Further, these wearable smart devices can communicate with remote devices to get diagnosed. It will help the medical fraternity constantly monitor and get alerted on the patient's conditions irrespective of the patient's location (Gadekallu et al., 2020). ICT would play a critical role in improving health care for individuals and communities worldwide (Numan et al., 2020). ICT-powered solutions would assist in closing gaps between healthcare and patients by providing new and more effective methods to access, share, and retain information, resulting in better quality treatment in less time. ICT also has the potential to improve healthcare system quality and prevent medical mistakes (Healthconnect-intl.org, 2020).

ICT is constantly adopting technological changes. It has evolved to the extent that it uses the information from various analytical and social media platforms to support the prevention of disease spread. It also encompasses the Geographical Information System to enhance its working on the problems related to epidemiology. Li et al. (2012) provided a brief description of how ICT might detect, monitor, and prevent emerging zoonotic disease outbreaks globally and in the country. This author has also highlighted how open-source and commercial technologies may be employed in pandemic prevention and human health protection activities. Shaikh et al. (2015) addressed the necessity of ICT-powered public health monitoring in dealing with increasing infectious disease threats, developing environmental and behavioral hazards, and shifting epidemiologic patterns in their study. Gomez and Katia (2010) presented ICT-driven solutions for local and global populations to promote quick response to public health catastrophes. In the case of pandemic epidemics such as HIV/AIDS, they have considered using ICT to satisfy public and health personnel's training and educational needs. They also highlighted how mobile technologies such as pagers, cell phones, Personal Digital Assistants (PDA), and tablet computers might play an essential role in crises, indicating ICT usage. Such gadgets in healthcare are referred to as mobile health (mHealth-mH). They have also stated that these mH related technologies are highly cost-effective when managing pandemics for a variety of reasons, including (a) mobile devices being reachable anywhere and at any time; (b) mobile devices being traceable through GPS; and (c) mobile devices being able to quickly obtain information (photos, video footages) and communicate in any situation.

An architecture for realizing the cloud-oriented healthcare support system has been proposed by Sandhu et al. (2016), this architecture is based on the fact and advantages of increasing usage of cloud computing technologies in day-to-day operations of information systems used to support the activities of healthcare systems. Similarly, Li et al. (2010) illustrated the method for connecting mobile-based SMS applications with eHealth and demonstrated the pandemic survivance technique in underdeveloped/developing countries. The authors have also demonstrated the method for identifying/tracing the pandemic strains. In Zhu et al. (2019) demonstrated the user-friendly PoC system that uses the advancements in IoT. The resulted data generated at PoC gets recorded through IoT and transferred to Android/iOS gadgets *via* Bluetooth/any other interfacing methods. The data can even be transferred wirelessly to the internet, which makes the data accessible immediately anywhere.

As a result, the suggested idea focuses on supplementing the PHC system with ICT-based interventions to allow cost-effective health care delivery in rural, urban, and distant populations. The ICT-based therapies can modify the health outcome and improve patients' health. The PHC is already staffed with skilled medical personnel such as nurses, midwives, and social workers. The PHC would be outfitted with generators and internet access. The infrastructure needed for a VHC would be built. A kiosk with specific cameras, monitors, microphones, and speakers would be installed in the PHC. Computers, electronic data storage, and scanners would be provided for effective data collection. A minimal diagnostic service would also be set up at the PHC. Patients would be given low-cost activity trackers, such as wearables, sensors, and mhealth/mH solutions. Patients would be taught how to utilize the activity trackers and smartphone applications. Standard operating procedures (SOP) for patient mHcare delivery will be developed and recorded in electronic form. Health care staff will be taught the use of ICT and the SOP. The EHR data would be aggregated into specialized data sets *via* disease-specific registries, but the patients' privacy and interactions would be protected. The datasets would be processed using machine learning and artificial intelligence to identify risk patterns and forecast illness outcomes and health progression. The trends discovered would aid health care professionals in refining SOP and developing evidence-based health policy.

The Virtual Health Clinic Infrastructure

Figure 1 presents the conceptual framework and approach for achieving Goal 1 and Objectives O.1.1–O.1.4 of the research concept. VHC is designed to have services like Virtual consultations (VC), Tele-pharmacy (TP), Virtual storage space (VSS), and Virtual Community (VCom). Virtual consultations would have two phases: In the first phase, appointments/consultations would be conducted *via* video-conferencing, and in the second phase, chat sessions or off-schedule consultations are considered. The EHR is made available to health professionals (HP) and patients during any of these sessions. In addition to the VC, patients may also have an in-person consultation with the HP. At the end of the appointment, the patient and the HP could set a date and time for the next session. The same approach is followed to support the Mobile assisted health care system using smartphones. The focus here is to aid the senior citizens in sticking to their medication regimes and sending reminders so that they do not skip the prescribed doses. This can also be used to inform the connected pharmacy to supply refills when low stock levels are reached.

Another service included in the VHC is tele-pharmacy (TP), which allows the pharmacist to accept electronic prescriptions and transmit drugs to the patient's house *via* courier. Patients can use TP to document their treatment history on charts and consult on available medications. The system includes a Virtual Storage Space (VSS) to hold verified information about numerous diseases, which links to other web pages for patients and HP. All links are classified according to their source and organized into categories. The virtual community (VCom) is where people may share illness information, raise awareness about various diseases, and express their thoughts or comments on articles and news items. This site is restricted to HP, where they may discuss their thoughts about their patients/cases.

VHC's architecture is divided into two stages. The first step is clinical infrastructure, in which the virtual web server is deployed to the clinic's existing demilitarized zone, which is then protected by a firewall and connected to the clinical information system network. HP connects to this server over the clinic's network. The second step is the home infrastructure, in which the patient connects to the server *via* a basic internet connection and, for security, a virtual private network (VPN).

Approach/Design of the Proposed Method

Figure 2 illustrates the proposed approach to achieve the research concept Goal 1 and O.1.1–O.1.4. The patient approaches a health care worker to register health complaints. Based on the complaints and screening, the health care worker identifies that the patient requires an expert's.

Consultation for a Diagnosis

The patient's consent is recorded, and the health care worker sets up a virtual consultation with a physician or specialist. The patient's history, current medical conditions, and demographics are stored in the patient's EHR. The doctor may require the patient to undergo laboratory tests, blood tests, etc. The concerned health care worker can do simple tests like blood pressure in the PHC. On completion of laboratory tests, the results are uploaded by the health care worker and made available to the consulting doctor. The reports could be text-based or even medical images. The doctor uploads the diagnosis, e-prescription, and general instructions provided for patient care. E-procurement of the medication and the refills would be done cost-effectively.

The health care worker generates a holistic treatment plan including important aspects such as medication, diet, exercise, weight management etc. An entire schedule of important dates for consultation, testing etc., would be generated for the patient. Educational material, the treatment schedule etc., are provided to the patient online, through Mobile based apps and/or social media apps such as WhatsApp. The healthcare workers would be

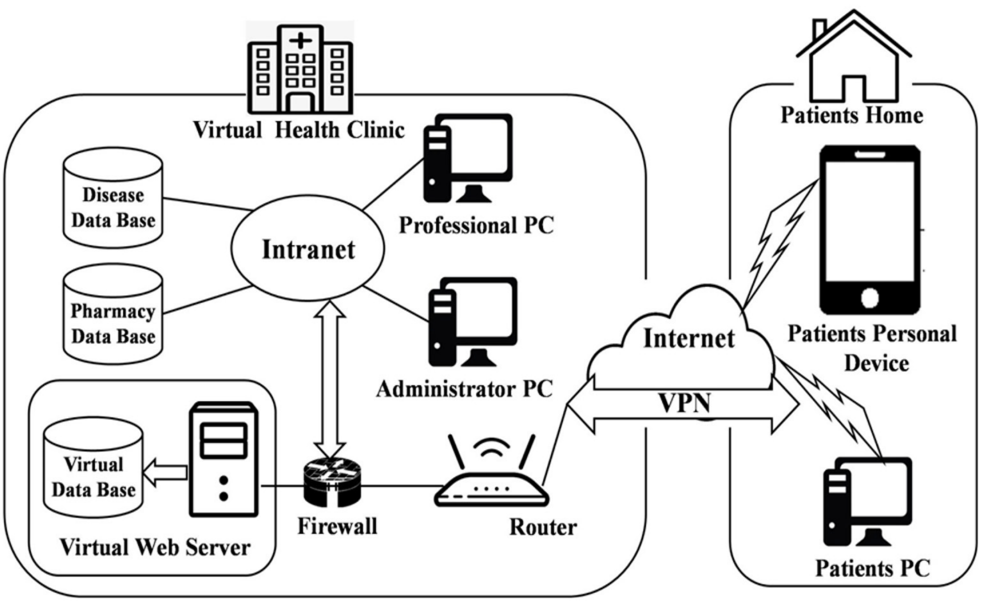

FIGURE 1 | Architecture of the Virtual Health Clinic (VHC) (Source: PAHO, 2011).

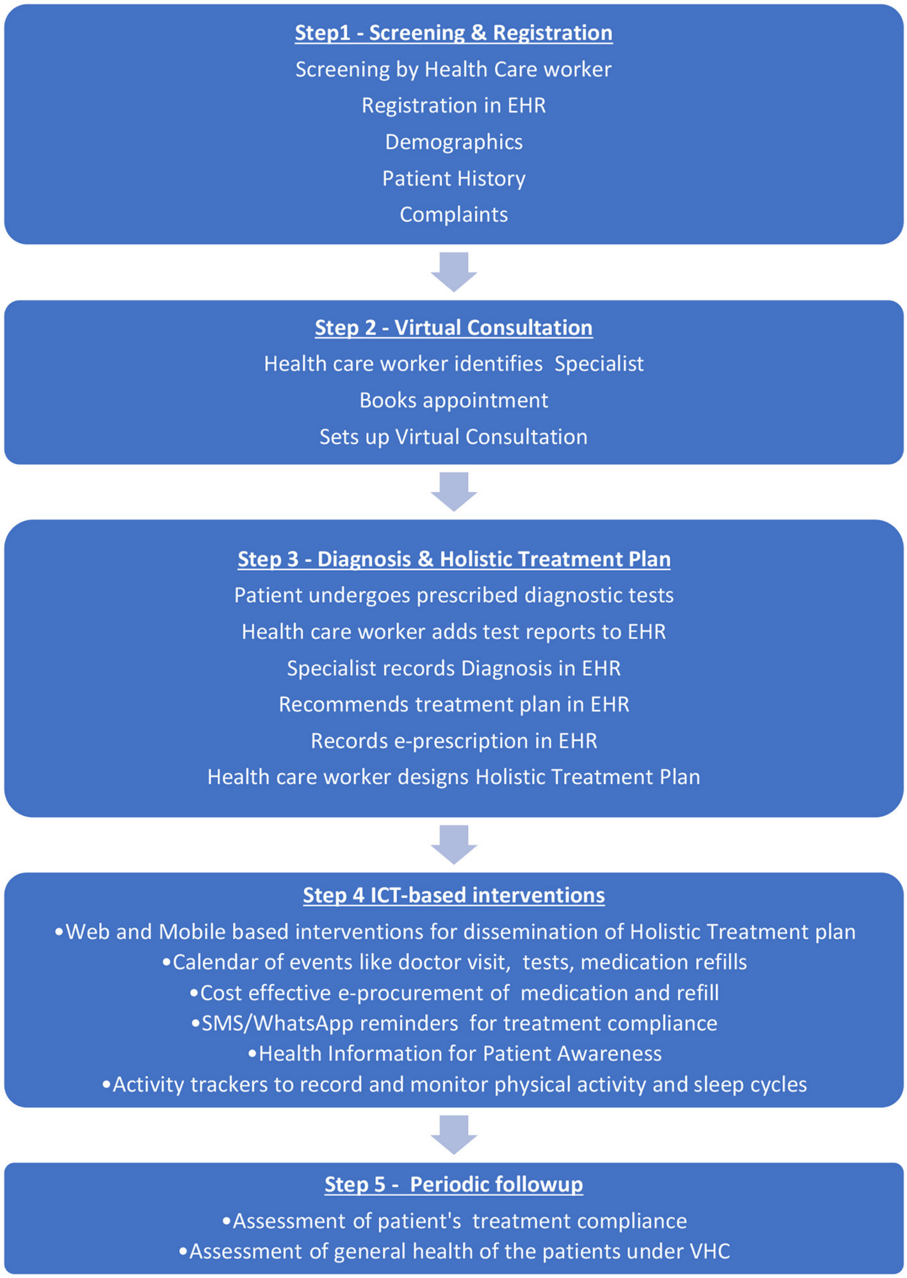

FIGURE 2 | The proposed Approach for Goal 1 and O.1.1 to O.1.4 Concept (Source PAHO, 2011).

trained to have a better health outcome. Periodically treatment compliance would be checked, and changes to the treatment schedule would be made based on patient recovery. Twice a year, the effectiveness of the mHcare initiative would be assessed to see if there is a significant improvement in patient health

Design/Conceptual Framework for Goals 2 & 3 and Its Related Objectives

The DMA helps to turn data into valuable resources in creating business value. The tools used here can handle a high volume of data incoming through various streams at various speeds that traditional databases cannot handle. These tools create value by mining a large amount of structured, semi-structured, and unstructured data to identify patterns that can help an organization manage costs and achieve high competency efficiently. The DMA architecture also leverages existing software component technology solutions such as Machine Learning, Deep Learning, Data Mining, Data modeling, and Data Visualization. The DMA chiefly comprises the following modules: Data collection module, Data organization module, Data Analytics, Business Intelligence module, and many more. The DMA is responsible for data collection, engineering, pre-processing, analysis, and dissemination of various research endpoints.

Commoditized cloud providers, private cloud providers, or other specific configurations of commoditized hardware are used in the architecture, cloud-agnostic solutions, open-source development and public availability, and compliance with industrial and commercial standards. The architecture gives users access to cutting-edge cloud services and tools, including discounted rates on industry-leading commercial cloud environments from STRIDES Initiative partners, including Amazon Web Services (AWS) and Google Cloud. Researchers have access to consulting resources, training, billing support, and an extensive catalog of cloud services to help with data computing, storage, sharing, analysis, and sustainability. The architecture establishes the internal authority of the open-source initiative, the open-source definition, and/or Open Systems Interconnection (OSI) approved open-source licenses as a prerequisite for adopting existing internationally recognized standards or establishing the internal authority of the open-source initiative open-source definition, an OSI-approved open-source licenses.

The proposed DMA architecture is shown in **Figure 3**.

One of DMA's primary functions is data access and discovery. The suggested DMA may search and explore data inside and across scientifically relevant research to enable popular use cases. The data might be in an organized, semi-structured, or unstructured format, and it could include textual, stream, and other types of data. DMA would collaborate with the other research at partnering institutions to generate and manage data to support adopted/commonly used data standards, formats, and vocabularies, as well as emerging technologies like AI, ML, and NLP, by implementing a query-based or pull-based model to fetch data from various authorized sources. The data may come from the Research centers, PHC, POC, medical institutions *via* electronic health records (EHR), or an open source that is acceptable for analysis after data engineering through contact tracing & tracking to prepare it for processing (Bengio et al., 2020; Dar et al., 2020; Ferretti et al., 2020; Kretzschmar et al., 2020; Piotto et al., 2021).

The proposed DMA includes a user workspace for storing, managing, computing, and sharing data and analytic findings with collaborators or the greater research community. Furthermore, the architecture provides a platform for users and researchers to contribute ideas or proposals that may be implemented by adhering to the DMA's correct principles and policies. It enables data to be pooled between users and researchers and other publicly accessible data *via* the DMA. DMA also provides open data Application Programming Interface (API) to researchers, making data accessible, comprehensible, and actionable, suited to the specific needs of authorized users or qualified researchers.

The DMA enables portable (including wearable) technology deployment. The tools and technologies will be shared with peer researchers/research labs or given free to willing participants. Additionally, open-data APIs will be built to share with diverse collaborators *via* responsive/progressive software applications (compatible with Web/Mobile). The proposed DMA work is open-source and may be accessible using GIT, GITHUB, or other commercial platforms. By providing a web interface and API access to data, tools, and computation and will be made compatible for interaction with other systems. DMA idea serves a wide variety of users, including computer illiterate and computationally adept users. This is accomplished through the availability of resources in the proposed architecture that comprises the web portal through which users can have secure access to the data/application. The web application would also include user manuals and a few sample demonstrations to help beginners and expert users become acquainted with the developed applications. **Figure 4** displays the data flow among many stakeholders to achieve a successful DMA.

Data Analysis

The DMA concept provides practical and strategic leadership for managing health science innovations in India and UAE. The DMA would work independently and synergistically to meet the purpose and identify the selected focus areas and strategic initiatives to create a rapid, reliable, and scalable research and innovation system. The specific activities mentioned below aim to achieve the DMA concept over 4–5 years.

The flow and interaction of the above activities are summarized in **Figure 5.**

- Deliver a software solution that would improve discoverability. A proposal request would be sent to all the consortium research centers, PHC, POC, and health practitioners, requesting an interface to access the data. Thereby, we can access the data by posing queries or processing the events generated by the data sources, such as Enterprise Data, 3rd Party Cloud Data, social media, etc., if there is an update in the data source. Anaconda tool can be used here.
- Assist the collaborating stakeholders as a technical resource for applicable use cases, including system capabilities to meet international data protection and anonymization regulations. This is accomplished by providing:
  - Support for data volume, variety, and computational requirements.
  - Measuring and Sharing metrics for performance and consumption.
- Encourage industry cooperation to harness current technology and solutions that are both cost-effective and sustainable through:
  - Creating a sustainable and transparent service cost model
  - Serving a variety of users.
  - Adherence to authentication and policies across the globe
  - Adherence to the data anonymization and data protection protocols while maintaining interoperability with other healthcare components.

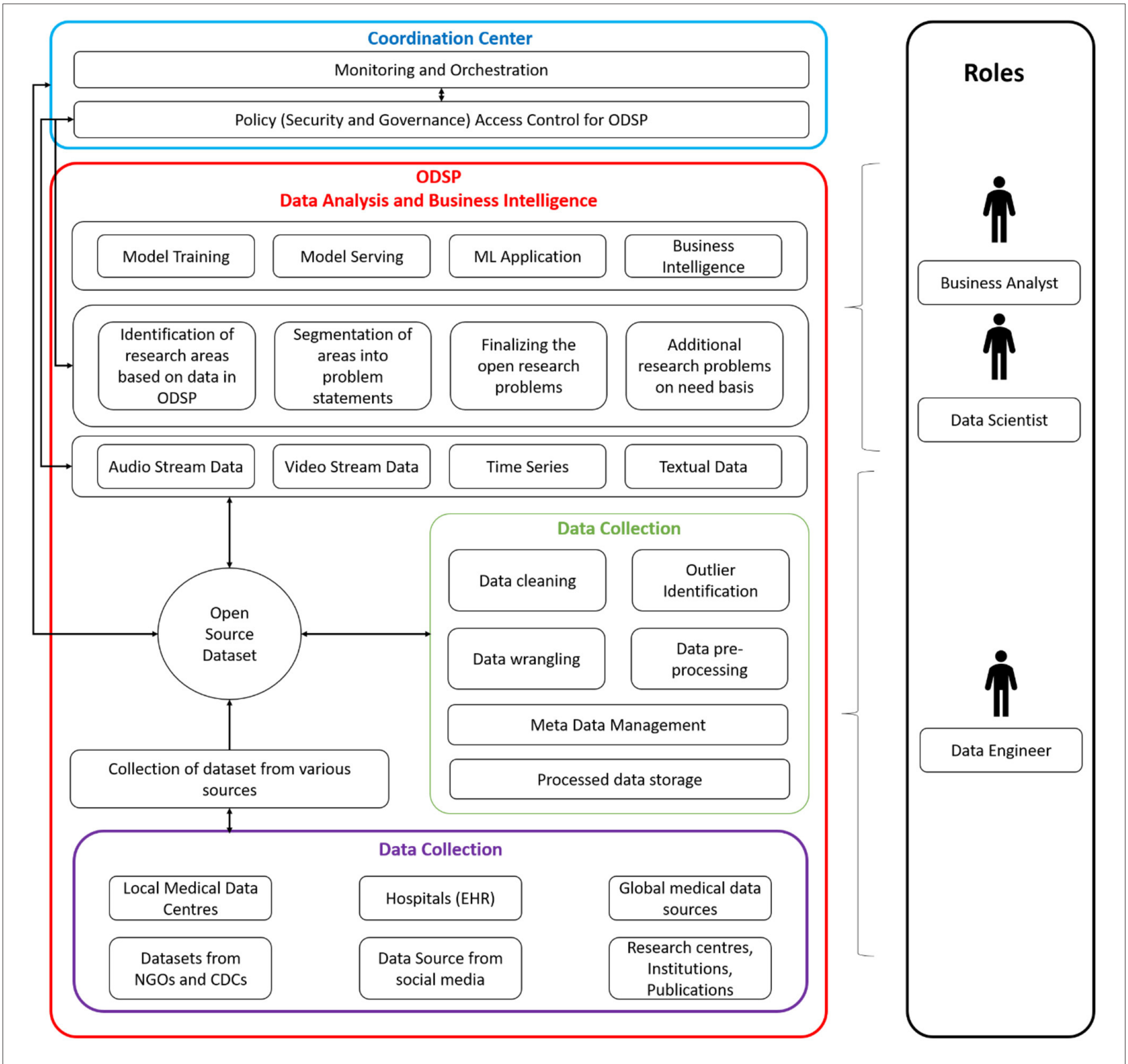

FIGURE 3 | Open Architecture of Data Management for Health Sector.

POLICY COMPLIANCE ISSUES

Data Standards

The development and deployment of digital health-related facilities are being regulated by National Digital Health Mission (NDHM). Additionally, the federal national health information architecture enforced the integration of information systems related to public and private health. For integrating systems, EHR with consistent Metadata and Data Standards (MDDS) would be supported by this policy. Affordable and innovative ICT would integrate health information into comprehensive EHR. The data quality and standards layer in **Figure 5** depicts the data quality standards applied for DMA.

The EHR would be standards-compliant, cost compliant, and enable effective and seamless data transfer between stakeholders. The typical HER data can be of one of the categories related to audio, video, X Rays, Images, etc. These data can be compressed and shared from PHC to healthcare professionals for diagnosis/further actions. ICT-based interventions like reminders using SMS/WhatsApp or other preferred social media apps for patient treatment compliance, recording symptoms, and identifying emergencies would be performed. All medical

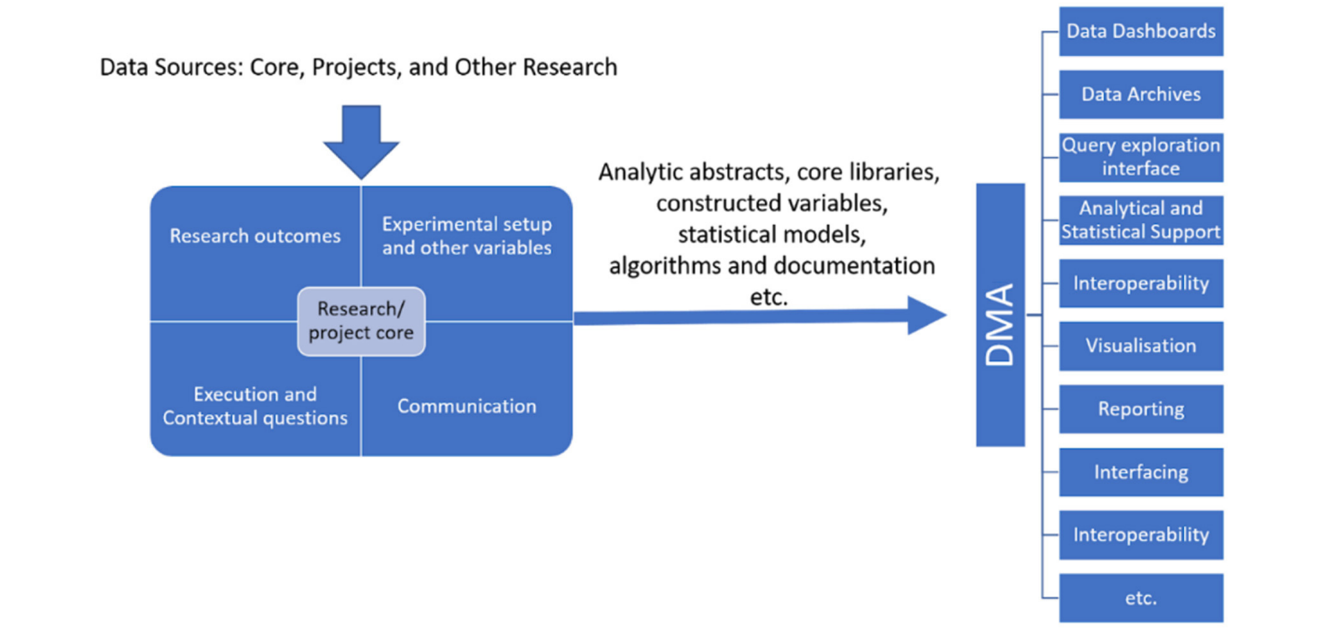

FIGURE 4 | Dataflow across stakeholders in UAE and India.

transactions occurring in the system would be recorded as immutable transactions on a blockchain. EHR-based privacy preserved datasets would be generated and published to study diseases. Analyzing these datasets would aid in public health policy design and implementation. Evidence-informed policymaking (EIPM - WHO, 2017) is considered a critical building block for enhancing the population's health in low, middle, and high-income regions/countries worldwide.

Ethical Issues (E), Legal Issues (L), Cultural and Social Implication Issues (CS) Would Be Handled in Data Collection, Data Usage and Result Dissemination to Stakeholders Handled Would Be Handled as Detailed Below

The concept is a healthcare concept, and patient data will be collected. Ethical issues concerned with this concept will be taken care of as given below:

- The consent form is prepared. The patient/user who participates in this concept will be informed about the details of the collected data, and the consent form's signature is taken. (E, L)
- The concept does not include clinical intervention because there is no need for ethical clearance. (E)
- For data collection from the ERP of the hospitals, a mutual agreement is required to be signed indicating what type of data is shared for this concept. (L)
- The collected data, if not in digital form, is converted to digital form. The data values like patient name, gender, religion etc., are watermarked/ hidden/removed to avoid personal details of a person/patient. This takes care of patient privacy protection. (E, L, CS)
- The data analysis from collected data will be published as a population study, not highlighting any person in particular. (CS, E)
- The data will be stored in a particular designated system to which the access will be password protected. The cloud storage will be under a specific collaborative organization's name. (L)
- Documentation related to the above is regularly maintained. (E, L)
- The regular periodical meeting will be conducted either online/or offline, and emails will be used to disseminate the results to the stakeholders.

Although the project is focusing on the technical and implementation issues from big data platform and solutions perspectives, we cannot overlook the issues created by its possible global implementations such as ethics, policies, and legal issues that face computer professionals and data scientists while working with health and personal datasets, as well as the project, will examine the related cyber security issues. Further, the ethical issues such as defining ownership of data, obtaining consent to collect and share data, protecting the identity of human subjects and their personal identifying information, and the licensing of data.

There are generally four matters of data acquisition and management that need to be addressed at the outset of a study: (1) collection, (2) storage; (3) ownership, and 4) sharing. These cases and role play present common scenarios that occur at various stages of data acquisition and management. It also includes acquiring sensitive data, sharing data with colleagues, and managing data collection processes.

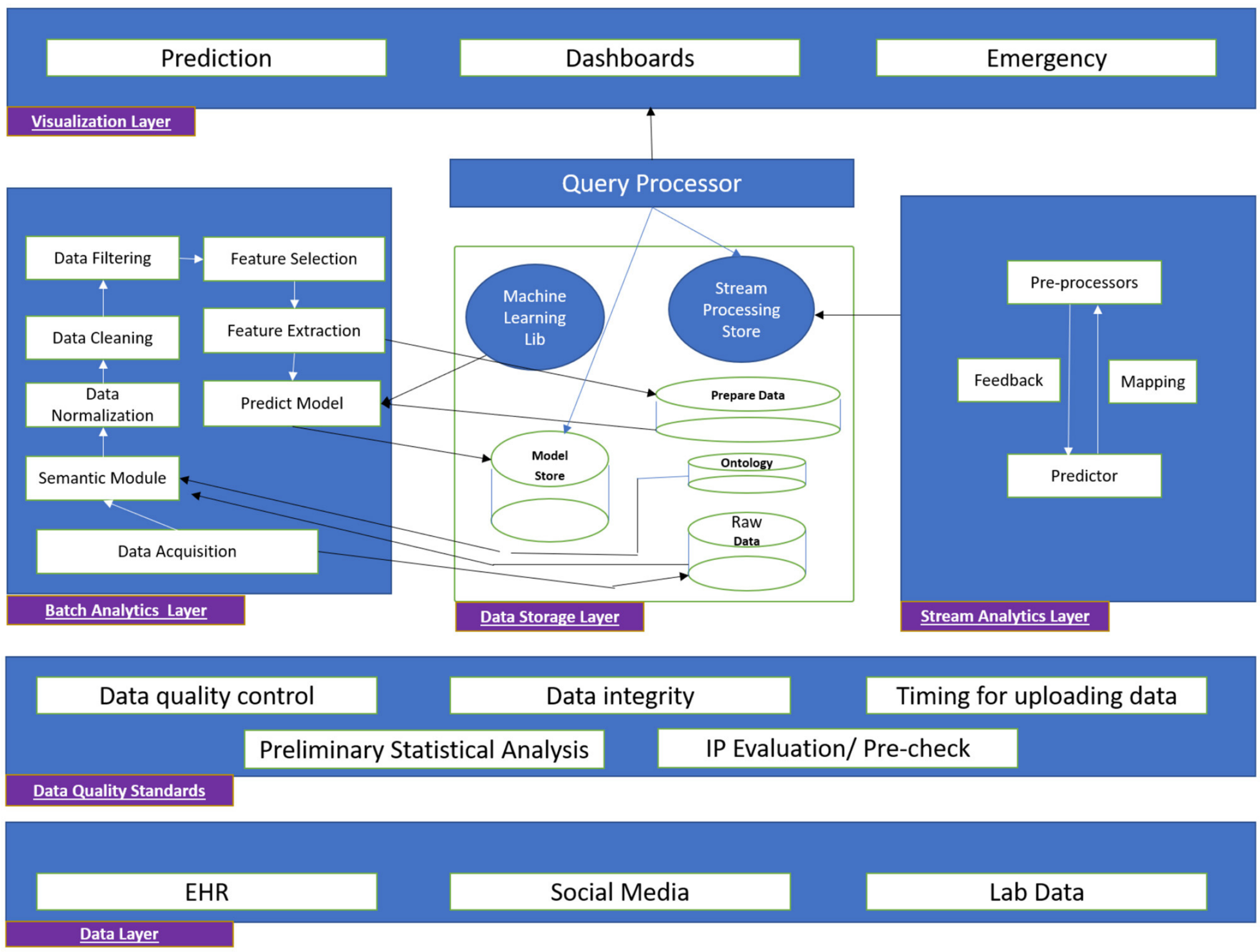

FIGURE 5 | Flow and Interaction of DMA Activities for research concept Goal 2 & Goal 3.

Data Management and Resource Sharing Plan

Tools, materials, and protocols from the research activities will be distributed to peers and interested research groups. The dissemination of research findings will be made public with suitable agreements. Based on the guidelines of the Indian and UAE governments, the policies related to sharing the data and conceptual information will be carried out. The research findings will be published in peer-reviewed journals as research manuscripts or through poster presentations or workshops will be conducted for all the interested research individuals/groups to disseminate the information.

Confidentiality

The UD, NMIT, MBRSM, and RMCH Offices of Research & Innovation (ORI) will manage all knowledge transfer sessions for resources generated by the researcher of all partner institutions and their collaborators. The ORI shall adhere to all relevant policies, principles, guidelines, and procurement regulations in making unique research resources freely available for research purposes to eligible persons and businesses. The ORI will assess and submit for patent protection on any subject innovation that may result from the research concept. Unpublished data that is considered proprietary or secret must be disseminated in accordance with a proper confidential disclosure agreement approved by the ORI. Patient data must be de-identified and disseminated according to ORI rules and relevant laws and regulations. Through an explicit "Software Sharing Plan," material transfer agreements and other licensing agreements will be formed to share resources across the academic community for non-commercial research usage (SSP).

Software Sharing Plan

The current proposal would explicitly commit to the following:

a. The software from the research concept will be accessible under an open license for research and academic purposes. The tools and findings from the research will be shared with biomedical researchers, research institutions, and the govt. Research laboratories.

TABLE 1 | Plan of action and research milestones.

Activity	**Year 1**				**Year 2**				**Year 3**				**Year 4**				**Year 5**			
	Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Formulation of functional requirements, VHC and DMA architecture, and design decisions	■	■																		
Documentation, dissemination of information among the stakeholders		■	■																	
Designing the plan and setting up the infrastructure			■	■																
Discovery of data sources and negotiation involving policies and rules to be incorporated for data sharing		■	■	■	■	■	■													
Raw data storage					■	■														
Data Engineering					■	■	■													
Metadata management & Warehouse identification					■	■	■	■												
Data classification					■	■	■	■	■	■	■	■								
Multiple algorithm creation and Data Modeling									■	■	■	■								
Data Analytics and Research problem identification Exploration of open data APIs									■	■	■	■								
Assembling all the modules into a unified model (VHC and DMA)													■	■	■	■				
Designing of VHC and Data Management policies and their implementation													■	■	■	■				
Formulation of data visualization and generation of reports																■	■	■	■	■
Self-Audit trails and Web Platform design																	■	■	■	■
Full VHC and DMA deployment and testing, Scalability of VHC and DMA Integration with Business rules, Enterprise governance																	■	■	■	■

b. The terms of would allow for the circulation and sale of enhanced or updated versions of the software and the addition of the program into other software packages.
c. To maintain community utility, the program would be transferrable so that other individuals or teams might continue development if the original investigators were unable or unable to do so.
d. Software availability parameters would include researchers' access to update the source code and share it with other peers. To increase the potential impact of the software developed in this proposal, the proposal would create a plan to manage and disseminate the improvements or customizations of their tools and resources by others using an open revision control and source code management system like GitHub to foster a community of code contributors and allow transfer to another individual/team. This strategy would also specify the conditions of the software availability enabling reuse, modification, and monetization to continue development.

INNOVATION

The first innovation in this research concept is defining and using a globally unique identifier (GUI) as a link between the objects containing clinical information and users. This ensures integrity and consistency (anti-tampering systems, anti-data tampering) between the information associated with users and, at the same time, ensures the anonymity of the same. The second innovation is about the extreme level of abstraction chosen to represent the GUI that allows direct mapping of the relationships between the objects in a format navigable by automated data mining and data analysis systems in DMA through the development of algorithms that are more accurate in identifying correlations between "clinical examinations" and "clinical diagnoses". These relationships would allow expressing the epidemic trend from the point of view of the clinical situation rather than from the epidemiological point of view (which is currently the trend). The third innovation is designing a framework that will provide the essential functions of contact tracing and anonymous GPS tracking through a VHC App. The design framework will focus on the vulnerability analysis of the possible sensor systems that can be used to provide a system as secure as possible within the limits of current technologies.

LIMITATION AND CHALLENGES

As a limitation, the proposed conceptual model might encounter deployment challenges and ease of adoption by the stakeholders and therefore requires hand-holding with all stakeholders for smooth and quicker implementation. The challenges and limitations are n dimensional. Dimensions can be increasing as the implementation of the proposed conceptual model start to progress.

On the broader note the major challenges of realizing the proposed conceptual model lies in the following points

- The disparate healthcare landscape and operational silos
- Rapid changes in healthcare data sources, types, volumes
- Positioning EMR/EHRs to absorb the increasing changes in data
- Stringent industry regulations on how data is handled
- Unique challenges faced by providers, payers, patients
- Need for more maturity in clinical and non-clinical data capture mechanisms

Few other limitations of realizing the proposed conceptual model can be Regulations and Compliance, Solving Regulatory Concerns, Volume Issues, Fragmented Data etc.

The proposed conceptual framework is applicable in multiple contexts and can quickly scale up to millions of users in multiple countries at an affordable cost. Heterogeneous devices leave the computational load to the distributed network. This will lead to countless possibilities for developing new solutions and new integrations with existing systems. The open-access and third-party applications that can be marketed and with a high market value will be, in addition to those already mentioned in the concept, will result in considerable savings for the public health system in multiple countries globally.

CONCLUSION

The proposed research concept aims at augmenting the PHC and POC system with ICT-based interventions to enable cost-effective healthcare delivery and potentially change the health outcome and result in better health for patients. The conceptual design is open, flexible, and scalable, and it allows users to access a wide range of digital materials. The data format is also extendable to access additional data/metadata, and the architecture is scalable to accommodate petabyte-scale federated discovery. Existing technology and resources are used to implement modular DMA. The uniqueness of the concept lies in the fact that the conceptual framework provides patients, including their data, access to specialist doctors from around the globe *via* the VHC; Improved health due to compliance to holistic disease treatment plans, and access to scientific health information; and Reduction in OoPE to patients.

RESEARCH MILESTONES (WORK PLAN - PLANNED ACTIVITIES WITH GANT CHART)

The concept will be led by Dr. Manoj Kumar (Department of Information Science and Engineering) with support from his NMIT colleagues viz., Dr. Jagadish Patil, Dr. K Aditya Shastry, Dr. Shiva Darshan (Department of Computer Science and Engineering); Dr. Nanda Kumar - from RMCH in India; in addition to Dr. Immanuel Azaad Moonesar from MBRSG-Dubai, and Dr. Nasser Al Muraqab from UD in Dubai. Prof. Ananth Rao from UD-Dubai, with the consortium members' assistance, will monitor and evaluate the concept work plan and outcomes for timely completion of the concept with financial assistance from MOH, DHA, and ADHA in UAE, and ICMR-New Delhi-India, besides the health industry partners. The plan of action and research milestones are detailed in **Table 1**.

AUTHOR CONTRIBUTIONS

AR laid the foundation and coordinated with the team to bring out the paper's content. His significant contributions are establishing the Background, Research Problem, and Objectives of this conceptual paper. KS and JP worked on Design/Conceptual Framework for Goal 1 and Objectives O.1.1 to O.1.4. SD and NS have worked on Design/Conceptual Framework for Goals 2 & 3 and its related objectives The sections Innovation, Limitation and Challenges, and Conclusions are contributed significantly by IM, NA, and MK has written the manuscript by coordinating with all the authors. He made all the edits, referencing, abstract, conclusion, and communication with the group and brought the contents of the manuscript to the current shape. SA has greatly contributed during the conceptualizing phase, his contributions are greatly in articulating the contents of this manuscript All authors are involved in conceptualizing the paper's contents and discussing the contents/design/flow of the paper. All authors contributed to the article and approved the submitted version.

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Limiting medical certainties? Funding challenges for German and comparable public healthcare systems due to AI prediction and how to address them

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Current technological and medical advances lend substantial momentum to efforts to attain new medical certainties. Artificial Intelligence can enable unprecedented precision and capabilities in forecasting the health conditions of individuals. But, as we lay out, this novel access to medical information threatens to exacerbate adverse selection in the health insurance market. We conduct an interdisciplinary conceptual analysis to study how this risk might be averted, considering legal, ethical, and economic angles. We ask whether it is viable and effective to ban or limit AI and its medical use as well as to limit medical certainties and find that neither of these limitation-based approaches provides an entirely sufficient resolution. Hence, we argue that this challenge must not be neglected in future discussions regarding medical applications of AI forecasting, that it should be addressed on a structural level and we encourage further research on the topic.

KEYWORDS

artificial intelligence, healthcare system (HCS), health insurance, adverse selection, medical certainties

Introduction

Artificial intelligence (AI) is finding its way into more and more areas of life, driving technological change and social development. In medicine, in particular, AI is enjoying great success. For example, the medical use of AI enables more precise diagnoses and allows physicians to determine the best treatment option for their patients (Topol, 2019b; Troisi, 2021)—thus reducing medical uncertainties. In addition, the use of AI leverages evidence-based predictions of individuals' health trajectories and precise determination of their disease risks, i.e., which disease they will most probably contract at what time and how badly (Chaari, 2019; Topol, 2019a)—thus producing new "medical certainties" (Mathews, 1995).

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By reducing medical uncertainties, the use of AI can improve medical practice (Pouly et al., 2020). By determining disease risks and producing medical certainties, the use of AI can enable healthcare systems—which are facing ongoing cost explosion and demographic change (Klöckner, 2021; Prasuhn and Wilke, 2021)—to plan more far-sightedly (Wang et al., 2019). If healthcare systems know in advance how many people will contract diseases in the middle to long term future and how many people will need medical treatment, they can hold available the necessary treatment capacities or financial resources, or help prevent those diseases. Thus, by determining disease risks and producing medical certainties, the use of medical AI contributes to improving and sustaining healthcare systems.

On the other hand, however, the medical use of AI may exacerbate existing funding problems in dual public-private healthcare systems (Corea, 2019).[1] When people know their disease risks with relative accuracy, though never perfectly, and have access to high degree of medical certainties, there is a risk that people with favorable health trajectories will switch from statutory health insurance—where they have to pay a premium based on individual income—to private health insurance—where their premium is based on individual risk—while people with overall unfavorable disease risks will stay in or switch to statutory health insurance. Such dynamics, known as "adverse selection" (Akerlof, 1970), challenge the funding of statutory health insurance (van Kleef et al., 2020).

This scenario raises the question of whether and how to counteract what others have called "the threat of adverse selection" (Jong, 2021). Taking an interdisciplinary approach, conducting conceptual analyses, thought experiments, and legal as well as moral assessments, we aim to answer this question in our paper. In particular, we will focus on the question if it is possible to counteract adverse selection by limiting the use of AI in medicine and establishing limits for medical certainties. However, we find that it is not possible to counteract adverse selection by using only limitations—and that instead it is necessary to rethink healthcare systems and their distinction between public and private healthcare systems.

To support our argument, we first conduct a conceptual analysis and show how the use of AI can, to a certain extent, reduce medical uncertainties and create new medical certainties by determining disease risks. Performing thought experiments, we then show how these new certainties can exacerbate adverse selection and challenge the funding of the statutory health insurance. We focus on the example of the German healthcare system, where certain individuals can choose whether to be part of statutory or private health insurance. After showing that existing safeguarding mechanisms are not sufficient to counteract adverse selection, we ask whether it is possible to counteract adverse selection by introducing limitations to the medical use of AI. In a legal and moral assessment, we will present four possible limitations and show why they are not feasible or not able to achieve this goal. In an interdisciplinary discussion we show that adverse selection can only be counteracted by fundamentally rethinking the structure of dual healthcare systems and reforming the distinction between statutory and private health insurance. We will then identify some limitations before summarizing our findings in a conclusion.

How does the use of medical AI produce new medical certainties?

Medicine is currently undergoing a process of pervasive digitization. Telediagnoses, electronic health records, remote surgery, as well as the introduction of digital twins are but a few among many examples of the novel opportunities. These new technologies promise to make medicine more accessible for many people (Flores et al., 2013) while also enabling a more personalized approach toward medicine (Chaari, 2019). The latest step is the introduction of AI into medicine (Topol, 2019a).

By AI, we mean self-learning algorithms trained with large amounts of data (so-called Big Data), to recognize patterns and draw conclusions from them. In recursive processes, the algorithms are given feedback on whether their conclusions are correct. They then use this feedback to learn, i.e., to rewrite their codes and improve their conclusion-making capabilities. Due to their computational power and learning abilities, AI can outperform humans in recognizing patterns in large amounts of data after only a short period of learning (Boden, 2018). That's why AI is used in many fields where large amounts of data need to be analyzed and evaluated.

Exemplary for the introduction of AI in medicine is its use in dermatology, tumor board conferences or for public health surveillance (Schwalbe and Wahl, 2020). Dermatologists usually build on many years of training and practical experience in classifying skin irregularities either as harmless or potentially dangerous. AI however, due to its automated image processing, is able to analyze images within seconds and compare vast databases of similar cases. This allows AI to determine skin irregularities faster than any dermatologist, and often with higher precision and less

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1 Some clarifications on how we understand certain terms related to healthcare systems: *Healthcare system*: Umbrella term for all institutions involved in financing medical treatment. Most follow a dual public-private structure; *Public healthcare system*: Part of the healthcare system to which all citizens belong compulsorily and which provides basic medical care; *Private healthcare system*: Part of the healthcare system which citizens can enter voluntarily by taking out additional insurance and which offers additional medical services; *Statutory health insurance*: German equivalent of the public healthcare system; *Private health insurance*: German equivalent of the private healthcare system with the difference that it is an alternative to statutory health insurance, not additional.

errors (Du-Harpur et al., 2020; Pouly et al., 2020). In another application, AI is used in tumor board conferences, where health professionals—often from diverse disciplines and with their respective expertise—get together to discuss available options for a patient's cancer treatment (Somashekhar et al., 2018). While even the most experienced physician has limited memory and reasoning capabilities, AI analyzes a patient's data, identifies relevant patterns, compares the individual case to many other cases, their treatments and outcomes, and thus provides treatment recommendations that help health professionals in these conferences make informed decisions (Bleher and Braun, 2022). A third possible application of medical AI is public health surveillance (Chiolero and Buckeridge, 2020). Here, AI technologies are applied to monitor the outbreak and/or spread of infectious diseases using various data sets, including official disease data, social media data, as well as individual movement and contact data. This AI-produced information not only reduces public health uncertainties about the spread and infectiousness of diseases, but can also help to find efficient countermeasures, to model and assess public health responses—and thus, at best, prevent further pandemics (Zeng et al., 2021).

In addition to reducing medical uncertainties in acute medical care or public health, AI produces new medical certainties by predicting with unprecedented precision, how people's health condition will develop. A case at hand is the use of digital twins—digital simulations of real persons based on their health-relevant biomedical (e.g., heart rate, blood oxygen saturation, blood pressure) and lifestyle data (e.g., exercise, physical activity, sleep cycles, consumption patterns, diet). This data is constantly updated by sensors in real time and modeled by an AI to create dynamic *in silico* simulations of persons—their digital twins. Even though digital twins are still in their infancy and are currently used primarily for research purposes, a wide range of studies are testing how they can be used medically (Ahmadi-Assalemi et al., 2020). For example, there are current studies in which digital twins are used to test in a virtual simulation how well a patient reacts to different drugs and which has the best efficacy (Björnsson et al., 2020). In other studies, digital twins are being used to perform virtual surgeries on a specific person and simulate whether and how he tolerates them and what benefits they would have for him (Ahmed and Devoto, 2021).

Further, by taking into account all data and extrapolating past and current health trends, digital twins promise fairly precise personalized predictions, e.g., determining the statistical risk of falling ill with particular diseases (Hafez, 2020) within a certain period of time with a high degree of accuracy (Huang et al., 2022). The latter can eventually span the entire lifespan and thus could allow for a complete profile of persons' health and their individual disease risks.[2]

Of course, neither a digital twin nor any other AI is currently capable of predicting a person's health trajectory with absolute accuracy or determining their disease risks beyond a shadow of a doubt. In fact, given various technical limitations of AI, e.g., incomplete or biased data sets, (unintentionally) discriminatory or opaque algorithms, it seems likely that AI predictions will *never* be able to provide 100% certainty about a person's health. But even though AI may never provide absolute certainty, the (limited) certainties it *can* produce are expected to have an enormous impact on the behavior of physicians or patients. For example, even diagnoses that are only 80% certain or treatment recommendations that are only 75% optimal will further help physicians make decisions and act. Similarly, it is likely that even a very good or a very bad health prediction, even if it is only so-and-so certain, will influence people's decisions. Especially if we assume that research about AI in medicine will continue to make progress in the coming years and decades—if recent and current trends in AI-research prove robust (Pouly et al., 2020)—and that AI-technologies will become ever better and more precise at determining their disease risks of people and predicting their health trajectory in the future, we have to assume that people will be increasingly influenced by these AI-produced certainties.

These new medical certainties, as well as the fact that individuals align their decisions and actions with them, although neither is ever completely certain, hold great opportunities. Equipping physicians and patients with highly accurate predictions about their health status and determinations of their disease risks for example, will enable earlier detection and treatment—even before a person falls ill. Ideally, diseases can be prevented completely because of very early measures taken and personal suffering can be spared (Vaishya et al., 2020). It also presents itself as an exciting opportunity for healthcare systems. By predicting how many people will contract diseases in the future and will need medical treatment, these new medical certainties can enable healthcare systems to plan more far-sightedly and safely (Panch et al., 2018; Schwalbe and Wahl, 2020). They can free up or create the necessary treatment capacities and financial resources—and withdraw them where they do not need them. Thus, the medical use of AI can mitigate prevalent cost pressures and sustain healthcare systems (Knorre et al., 2020). In all these sectors, AI can and will increasingly

2 In addition to digital twins for individuals, there are also twins for entire cities or societies (Deren et al., 2021). Similar to AI-technologies for public health surveillance, these digital twins are created from the real-time data that its members produce which is modeled into a dynamic representation of the city or society. This digital twin of society can be used, for example, to simulate how certain diseases might spread in a society or to predict trends in current infectious diseases (Kamel Boulos and Zhang, 2021). In the context of the COVID-19 pandemic, for instance, such digital twins were used to predict the spread of COVID-19 within societies (Wong, 2021)—and to simulate which measures would be most effective in containing its spread (Sahal et al., 2022). This is how digital twins have created medical certainties for public health.

take over functions ranging from pure data analysis and decision support to the complete assumption of decision-making. This does not necessarily mean that human actors like physicians will disappear from the medical field nor that this is the aim of this process (Topol, 2019a; Araujo et al., 2020).

Nevertheless, the influence is so immense that fundamental restructuring is to be expected. Correspondingly, the new medical certainties generated by AI also raise challenging questions. One first question is how certainty about one's own future health development affects people, their self- and world perception as well as their psyche and life planning—especially if AI predicts unfavorable health developments (de Boer, 2020; Tretter, 2021). A second question is, how these effects on people have a further impact on (health) policy making (Margetts and Dorobantu, 2019; Coeckelbergh, 2022). Another question of primary concern to us is how increasing medical certainty will affect healthcare systems and their funding. In particular, the medical use of AI may exacerbate adverse selection, where individuals with low risk of disease migrate to private health insurance—which might lead to funding problems for statutory health insurances.

How do new medical certainties challenge healthcare systems?

We focus on the second question and outline the challenges that new medical certainties pose for healthcare systems, we will first describe how healthcare systems are funded on a solidarity basis. We focus on the example of Germany with its dual healthcare system of statutory health insurance on the one, private health insurance on the other hand and the option to switch between the two. While both types of insurance systems in principle offer similar insurance against health related cost risk to their policyholders, they mainly differ in how they calculate their premiums. After describing this difference and considering which form of insurance is of interest to whom, we present how new medical certainties can lead to adverse selection—and how this challenges the funding of statutory health insurances.

Healthcare system in Germany—statutory and private health insurance

Almost all healthcare systems in the Western world are funded on a solidary basis (Rice, 2021; Schölkopf and Grimmeisen, 2021), i.e., their members pay a regular premium into a common insurance pool. If a person falls ill, the financial cost of recovery, regeneration and other cost is paid from this common insurance pool. By covering this cost through their regular premiums, the members of the healthcare system in the end support each other in solidarity.

In the German healthcare system, the way of calculating the individual premiums diverges between statutory and private health insurance. The premiums in private health insurance are typically calculated on the basis of risk of disease (Müller-Peters and Wagner, 2017). If a person has a high risk, she has to pay higher insurance premiums, with a low risk lower insurance premiums. The individual disease risks of persons are determined by private health insurance companies on the basis of certain statistical and behavioral data (Igl and Welti, 2018)—for example, pre-existing conditions, age, and if they smoke (Albrecht, 2018; Hoffmann, 2021).

The premiums in statutory health insurance instead follow two subsidization mechanisms. First, the insurance premium is not calculated according to the individual risk of disease, i.e., people with high risk do not pay higher premiums than people with low risk of disease. The reason for this "subsidizing risk solidarity" (Lehtonen and Liukko, 2011) is to avoid placing the extra burden of high insurance premiums on individuals with a high risk of disease. Instead, insurance premiums are based on individual income, i.e., people with high incomes pay higher premiums than people with low incomes. The reason for this "subsidizing income solidarity" (Lehtonen and Liukko, 2011) is to prevent, that people with a low income have to pay a large share of their income for insurance contributions, while people with a high income have to pay only a small part of their income for insurance contributions. In principle, policyholders currently have to pay 14.6% of their contributory income to their GKV (§ 241 SGB V). If a statutory health insurance is not allocated enough funds, for example because it insures too high risks, it must levy its own additional contribution to fill this gap (§ 242 SGB V). Beyond that, there is no regulatory framework linking the level of disease risk and the income-based premium.

Most Western countries with the exception of the United States have public healthcare systems and citizens are required to participate in them (Rice, 2021; Schölkopf and Grimmeisen, 2021). In almost all of these countries it is possible to contract *additional* private health insurance for services not covered by public healthcare. In some countries, however, citizens also have the option of opting out of public healthcare systems and instead acquiring private health insurance exclusively. This, for example, is possible in Germany, where currently 88.2% of the citizens are part of the statutory health insurance, its public healthcare system (GKV-Spitzenverband, 2021) and only 5.2% are insured exclusively with private health insurance.

Interests of policy holders

Healthcare systems produce a benefit for their members. The person is financially protected in the event of disease and does not have to pay by herself for occurring cost. Likewise, being part of a healthcare system generates cost for individuals in the form of their premiums. People weigh financial cost and benefits, among other factors (Richter et al., 2019), in order to identify the optimal choice when they are seeking insurance since it is in their rational self-interest to pick the contract which provides them with the largest overall benefit (Corea, 2019). Since, as noted above, the benefits in statutory and private health insurance are roughly the same—both offer basic health coverage, private health insurance offers some additional benefits (§ 11 SGB V, § 192 VVG)—it is mainly the cost that is decisive for the choice between the two types of insurance (Lünich and Starke, 2021).

For this choice policyholders will look at their individual disease risks and compare how much they have to pay in different insurance systems. Individuals with a high risk of disease—potentially, for example, those with pre-existing conditions or diseases—might take into account that they pay more in private health insurance, where premiums are calculated based on individual risk. In turn, individuals with low risk of disease may see that they have to pay less in private than in statutory health insurance.

As long as the individual risk cannot be determined precisely, i.e., as long as there is uncertainty about the individual risk, the choice between statutory and private health insurance is kind of a "gamble"—both for the individuals and for the institutions. Neither individuals nor insurers know the exact person's risk, i.e., how much cost they will approximately generate and how high their premiums must be to cover this cost (Jong, 2021). This phenomenon is not limited to medicine, it is also known in other fields, like finance.

Now, if AI makes it possible to predict a person's health trajectory and accurately determine her risks and if many people have access to AI and its predictions, this medical uncertainty gradually fades away. This can have effects on the person's decision between statutory or private health insurance—already without AI being intended to replace decisions. This is because people generally have confidence in the fairness and usefulness of AI-assisted decisions, even if they are of high impact. In fact people often evaluate these decisions taken by AI par or even higher in comparison to human experts (Araujo et al., 2020). Now if AI predicts that a person's health will develop unfavorably and that she has a high risk of disease, she may obtain the certainty that due to her risk and income it would be financially more favorable for her to get statutory health insurance. Conversely, if AI predicts that a person's health will develop favorably and that she has very low risk, it would be advantageous for her to be privately insured and to pay an individualized premium (Figure 1).

This can be illustrated using a simplified example—simplified as it considers only the risk of one disease and not the cumulative risk of all diseases as would be relevant for healthcare systems. For example, suppose an AI were to calculate a 25% risk for a middle-class male in his late 20s living in Germany, to develop cancer during his lifetime. His risk would then be significantly lower than the 47.5% average lifetime cancer-risk for an average German male (SwissLife, 2020). His significantly lower disease risks would mean that his risk-based premium in private health insurance would also be very low. Now, if he did not earn so little money that his income-based premium of statutory health insurance would be even lower, having low disease risks would be a strong incentive to choose private health insurance. However, if the AI did not diagnose him with a 25% risk, but with an 80% risk, this would have the opposite effect on his choice. As his risk of illness increases, his risk-based premium in private health insurance would also increase significantly. Now, if he did not earn so much money that his income-based premium of statutory health insurance would be even higher, his high risk of disease would be a strong incentive to choose a statutory health insurance. However, the latter is hardly possible in Germany as the so-called "Beitragsbemessungsgrenze" sets a limit for the amount of income considered for calculation [§ 223 *Section* 3 SGB V (Federal Ministry of Health, 2020)]. Any income above 58,050 Euro in 2022 (Bundesregierung, 2022) must not be considered in income-based premium calculations. Using the example of cancer, it is illustrated how differences in income and (cumulative) disease risks can affect a person's premium as well as her choice between private health insurance (and their risk-based premiums) and statutory health insurance (and their income-based premium).

Adverse selection and funding issues for public healthcare systems

When individuals obtain new medical certainties regarding their individual disease risk in relation to their expenses for insurance premiums (which are already certain information to them), this enables them to perform a cost-benefit assessment that is more precise than before. The opportunity can be beneficial for "low risk" individuals. If their disease risks are below average, they might have an incentive to switch to private health insurance where they might be able to get insurance for lower premium payments after revealing their low risk profile. For "high risk" individuals already in the private health insurance, on the other hand, the new medical certainty might be a concern. They can expect a significant increase in their individualized premium rates if the private insurer obtains access to the medical information as well.

The novel possibilities of precisely estimating individual risk can also pose a major challenge for the statutory healthcare system as a whole. That is the case for countries—like Germany—where people are able to opt out of the public healthcare system and instead obtain private health insurance. A significant portion of (low risk) individuals would have an incentive to take advantage of this option, and to get private

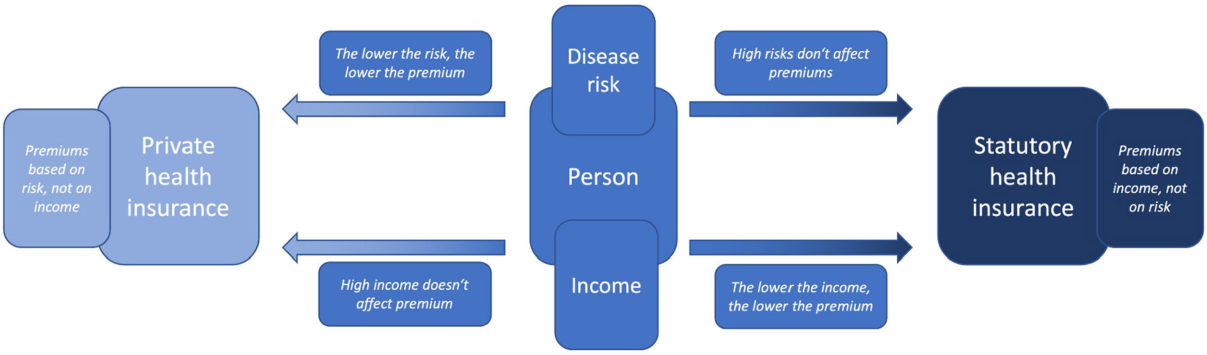

FIGURE 1
Illustration of the choice an individual may face between either statutory or private health insurance and the according price determinants income or health risk (created by the authors).

health insurance in order to save money. Likewise, "high risk" individuals in private health insurance have an interest to switch to statutory health insurance. This effect triggers a splitting development: Individuals with higher disease risks remain in, or switch to, the statutory health insurance while individuals with lower disease risks move toward the private health insurance or remain privately insured if they are already. This phenomenon is an incidence of "adverse selection" (Bitter and Uphues, 2017). In the decades following George Akerlof's seminal "lemons" paper (Akerlof, 1970)—representative for the work that led to him receiving the 2001 Nobel Prize in Economic Sciences—economists have thoroughly studied the issue (Browne, 1992; Simon, 2005) also with regard to health insurance. Since asymmetric information is *the* underlying factor for adverse selection, and since asymmetric information is usually highly prevalent in insurance markets, the issue bears special significance for these markets. Empirical studies have pointed out how adverse selection may generate societal costs and welfare loss (Cutler and Reber, 1998).

In the particular case of statutory health insurance, adverse selection is a concern as it might gradually shift the equilibrium between "low risk" and "high risk" individuals toward a higher average risk. When the average risk (per insured person) increases, so does the average expected cost (per insured person). Since the insurance system must cover its expenses and balance its books in the long run, this leads to rising premiums. When premiums rise, this can set in motion a self-reinforcing feedback loop (or *vicious cycle*), as the higher premiums mean that, now, an even larger share of people has an incentive to opt out and the cycle begins anew. In a similar context, Cutler and Zeckhauser (1998) used the term "adverse selection death spiral" to describe such a potential development.

With respect to funding issues of statutory health insurance (Bitter and Uphues, 2017), it is further important to keep in mind that "low risk" individuals pay—on average—more into the statutory health insurance than they get back in covered medical cost. Thus, the health insurance receives a net revenue gain from "low risk" persons which enables the insurer to subsidize high-risk persons who generate more cost than revenue (as their risk is higher than the one they pay for). To counteract the loss of revenue due to adverse selection, statutory health insurance must thus raise premiums significantly which jeopardizes the purpose of statutory health insurance, i.e., to safeguard general access to medical treatments especially for poor or vulnerable individuals (Prasuhn and Wilke, 2021). If the vicious cycle is allowed to continue unopposed, this would have the potential to ultimately derail the whole funding of the health system, since premiums might increase to unprecedented heights and the group of people able to pay them would continuously dwindle.

This process of how AI produces new medical certainties from medical data and how this ultimately exacerbates adverse selection can be illustrated in Figure 2.

Why are current tools not sufficient to counter adverse selection?

As the previous sections have shown, AI produces new medical certainties by determining individual disease risks. These new medical certainties enable people to weigh the cost and benefits of both types of insurance systems more precisely and to choose between statutory and private health insurance. This possibility bears the risk that persons with low risks opt out of statutory health insurance and choose private health insurance only. Adverse selection poses a threat to statutory health insurance, as it jeopardizes their funding in the long term.

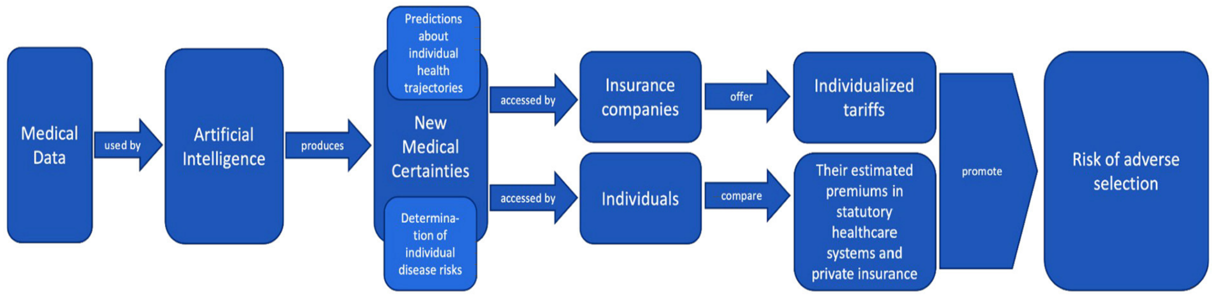

FIGURE 2
Illustration of how AI produces new medical certainties from medical data, how these certainties are used by insurance companies and individual policyholders, and how this ultimately exacerbates adverse selection (created by the authors).

Within the healthcare system in Germany, there are some mechanisms that might be able to counteract adverse selection and cushion the challenge it poses to the funding of statutory health insurance. Those mechanisms were not designed to specifically tackle threats due to the use of AI in medicine, but to safeguard and sustain reliable funding.

First, not every person is free to sign a contract with private health insurance. Citizens are generally obliged to have health insurance (§ 193 VVG) while most of them are obliged to take out a statutory health insurance (§ 5 SGB V). Only certain circumstances exempt people from this obligation and allow them to acquire private insurance exclusively (§ 9 SGB V). The exempting criteria include an income threshold-—64,350 Euro in 2022. It also applies to civil servants, clergy persons and full-time self-employed individuals. The Federal Ministry of Health is counting on a 10.4% share of voluntarily insured members in the statutory health insurance in 2021 (GKV-Spitzenverband, 2021). According to the Federal Ministry of Social Security, however, the share of contributions to statutory health insurance paid by voluntarily insured members will be 21.3% in 2021 (Bundesamt für Soziale Sicherung, 2021). That is, while only these people have the option to switch insurance, they, in particular, contribute disproportionately much to overall funding of statutory health insurance.

Furthermore, private health insurers are subject to various legal principles that, at least partially, impede insurance premiums from being exclusively based on individual disease risks and to offer individualized so-called *pay-as-you-live-tariffs* (Bitter and Uphues, 2017; Brömmelmeyer, 2017; Albrecht, 2018; Hoffmann, 2021). Without an offer of an individualized insurance premium, there is less incentive to leave the statutory health insurance. As a consequence, there is less leeway for adverse selection.

By limiting how many people can switch and how much insurance companies can individualize their tariffs and premiums, legal regulations can counteract adverse selection to a certain extent. However, they can never prevent adverse selection, as they cannot stop private insurers from determining individual risks or offering risk-based tariffs. Rather, the latter is their legally mandated task [§10 KVAV (Albrecht, 2018)].

This shows existing mechanisms to be sufficient to attenuate some short-term adverse selection. These mechanisms are, however, not able to cushion or counteract widespread and persistent adverse selection, with large proportions of people with low disease risks opting for private health insurance and large proportions of high-risk people opting for statutory health insurance. Unfortunately, it is exactly the latter that poses enormous long-term threats to the funding of statutory health insurance and calls for other mechanisms to counteract adverse selection.

Using bans or limits to counteract adverse selection?

One way to counteract adverse selection could be to prohibit the medical use of AI. Several open letters (Conn, 2017), governance papers (Datenethikkommission, 2019), and regulation drafts (European Parlament European Council, 2021), discuss banning research on and use of AI in other fields where it is considered to be too dangerous. So far, however, such demands have primarily referred to military AI or "certain AI systems intended to distort human behavior, whereby physical or psychological harms are likely to occur" (European Parlament European Council, 2021). Regulation targeting medical use of AI has been proposed in China (De Wei, 2021): The draft law "Announcement on Public Comments on the Detailed Rules for Internet Diagnosis and Treatment Supervision" in Article 13 aims to significantly restrict the use of AI for internet diagnoses of patients (National Health Commission Medical Administration Hospital Administration, 2021).

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Adapting a similar approach could prevent AI from producing medical certainties and determining disease risks that in turn enable adverse selection. Such prohibition would, however, also prevent medical improvements, inhibit technological progress and would thus constitute a handicap in international competition between states (Oh et al., 2021). Furthermore, medical certainties can also be created without the use of AI, e.g., by making use of genetic testing (Paul et al., 2014). Ultimately, banning such useful technologies seems problematic from the perspective of liberal and democratic states, making it a rare exception that can only be considered for extreme cases, such as the editing of the human germline genome (Boggio et al., 2019).

Rather than completely banning medical use of AI, one might think about *limiting* the medical use of AI. A German approach on limiting AI in healthcare would have to be integrated into both the German and the European AI strategies. Both strategies provide for strong support of AI research, also and especially in the healthcare sector (European Commission, 2021; Bundesministerium für Gesundheit, 2022). The EU has recently presented a draft on the general regulation of AI, which centrally provides for a risk assessment of AI uses. This assessment leads to a ban or to certain framework conditions for the use of AI (European Parlament European Council, 2021). On the one hand, this conditions refer to the input level and provide for quality standards for the AI training data. On the other hand, they refer on the output level and provide that the results of AI systems should be verifiable (Ebert and Spiecker gen. Döhmann, 2021). Overall, this draft has been positively received by Germany (Deutscher Bundestag, 2022) and although the regulatory project has not yet been finalized it seems like both, Germany and the EU, are walking the same way on implementing AI in healthcare system. Nevertheless, this approach is recognizably at odds with our critical analysis of medical certainties, and is more likely to promote them, as it primarily refers to conditions which promote more precise predictions of AI. Accordingly, the approach of limiting certainty-producing AI can complement the regulatory approaches of the EU and Germany. The desired goal would be to limit AI in a way that allows it to continue to produce medical certainties that are useful for medical practice, but prevents it from producing a high degree of medical certainties that could exacerbate adverse selection. Since this is a rather non-specific idea so far, the question from the perspective of a regulating entity is: which regulatable aspect of AI could be limited in order to counteract adverse selection without rendering AI completely useless for medical purposes? In this chapter, we will therefore discuss the four most promising aspects that appear to be causal for the occurrence of adverse selection and thus have the potential for limiting regulation.

Limiting the computational power of AI

A starting point would address the technical framework. A key technical aspect behind the great potential of AI is its underlying overall computational power: the more processes an AI system can perform in a given period of time, the more data it can analyze and the more accurate predictions it can theoretically make. Higher computational power has the potential to create more medical certainty, which, as described, favors adverse selection. By limiting the computational power of medical AI, one could prevent it from generating a high degree of medical certainty and thus counteract adverse selection (Hwang, 2018).

However, a closer look reveals that the presumed direct correlation between computing power and medical certainty exists only loosely. Dermatological analysis *via* smartphone app shows that for special tasks comparatively little computational power can produce high levels of medical certainty (Topol, 2019b). Conversely, AI equipped with immense computing power but not operated by expert persons or is equipped with insufficient data (e.g., too little or too inaccurate) might produce little to no medical certainty.

Tackling adverse selection by limiting the computational power of medical AI would be pointless at best and harmful at worst. It would be pointless because trained personnel with good data could produce high levels of medical certainty, even with little computational power. It would be harmful if the limitation of computational power—despite good data and the use by trained personnel—would lead to inaccurate prognoses, stand in the way of the success of medical treatments and thus endanger human lives.

Limiting the output of medical AI

Instead of addressing technical frameworks and limiting the computational power of AI, another approach would focus directly on the output of AI (Swedloff, 2014). This would avoid the problem of regulation overlooking aspects that are relevant to producing medical certainty or, conversely, overemphasizing irrelevant aspects.

If the AI were to produce levels of medical certainty that did not carry the risk of exacerbating adverse selection—e.g., because the person's high individual disease risks would not correspond with low premiums in private health insurance (Swedloff, 2014), its medical use would be permissible. Conversely, if the AI were to produce a level of medical certainty that might exacerbate adverse selection—e.g., because the person's low individual disease risks would correspond with low premiums in private health insurance, it may not be used for such risk. Accordingly, such an order would be rendered absurd by the certainty already produced. At first glance, this seems to be an appropriate starting point for regulation. However, the content of the regulation is not technically feasible.

A limitation of certainty in the constellations just described, which show a risk of adverse selection, could be that AI may not be used for such risk predictions. However, this paradoxically requires medical certainty to be produced first in order to subsequently allow banning this production of certainty.

Limiting access to medical certainties

A third option would not try to set a limit on AI or its medical use but would rather focus on the medical certainties produced by it. If these certainties could exacerbate adverse selection—e.g., if the individual disease risks would correspond with low premiums in health insurance, the patients' access to them could be limited. While physicians might still be allowed to access these medical certainties and use them for treatment purposes, the patients themselves might not be granted access to their medical certainties. This would prevent them from updating their assumptions regarding their individual disease risks and leaving statutory health insurance.

However, this approach appears paternalistic and not in line with a liberal society. After all, people have a fundamental right to obtain their own medical information. To restrict this right would constitute a legal novelty and require sound justification. To find such justification might turn out to be difficult since one's own medical information is rather close to the very core of personal rights. After all, if information about her medical risks is withheld from the patient, the patient may become suspicious and draw conclusions about her level of risk.

Finally, we can expect to see private companies offering direct-to-consumer AI based medical prediction—similar to *23andme* and *Ancestry* business models in the context of genetic testing (Thiebes et al., 2020). Given these direct-to-consumer opportunities, it will be difficult to limit individuals' access to medical certainties.

Tying access to certainties to agenda-driven conversations

A fourth approach to counteract adverse selection would acquaint patients with the advantages of statutory health insurance over private health insurance and also appeal to their individual solidarity. This could take place during the physician-patient conversation, when patients are informed about their medical risks and certainties. The physician could appeal to the conscience of the patients (Moloi and Marwala, 2020), point out the high value of the solidarity-based nature of statutory health insurance or show how paying individual one's premiums helps to save lives and preserve the quality of life of others. This approach could even be legislated in the form of a general duty to inform, requiring physicians to communicate medical risks and certainties to their patients exclusively in a conversation that must include the above directions and appeals.

There are several problems with this approach. First, it places the responsibility on physicians to prevent adverse selection. This represents a massive non-specialist overload on physicians. It risks undermining the trust relationship between doctor and patients as the patients could no longer be certain whether a doctor has only decided exclusively in their best interests or if a doctor actually bears diverging objectives in mind. Furthermore, this approach would be an attempt to solve a structural problem on an individual level—which appears to be unsustainable.

Discussion

We have shown that neither banning or limiting AI and its medical use nor limiting the access to or use of medical certainties seems to be a viable approach to counteract adverse selection. The different possibilities of banning and limiting, as well as the reasons why they fail to counteract adverse selection, can be illustrated (Figure 3).

As all discussed limiting options fail to solve adverse selection, policy-makers might want to consider more comprehensive approaches. After showing that adverse selection is a fundamental problem of the dual public-private healthcare system and does not arise only as a result of AI, we will propose in this chapter that it can only be counteracted at a structural level—by rethinking healthcare systems' dual nature. In Germany, there are already some debates on whether and how to restructure the national healthcare system. After introducing these discussions and briefly showing how our results may contribute to them, we will ask for whom our considerations are relevant—only for the German context or also for the healthcare systems of other countries—and survey empirical evidence to validate our theoretical discussion.

Ongoing debates about structural reforms of the healthcare system

We have assumed medical AI to produce certainties that can *exacerbate* adverse selection in statutory health insurance. This wording indicates that adverse selection is not generated by the use of medical AI in the first place. Instead, adverse selection is a general problem of dual healthcare systems, where individuals have the option to switch between statutory and private health insurance (Cutler and Zeckhauser, 1998). Thus, to effectively

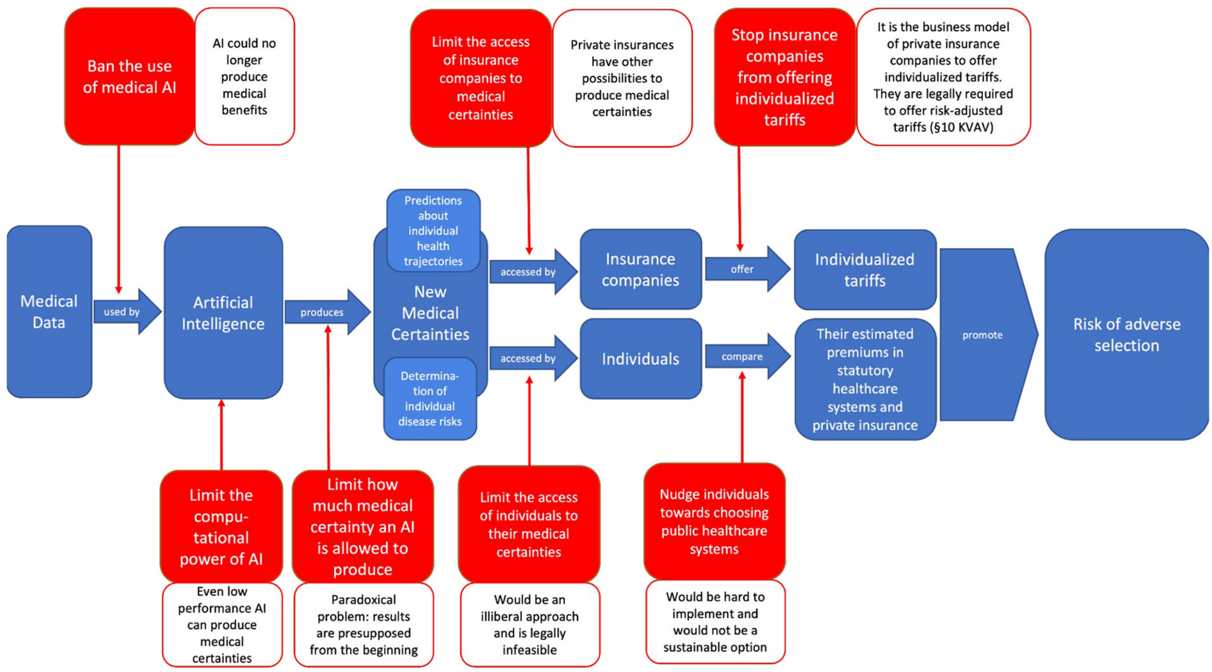

FIGURE 3
Illustration of the different possibilities of banning and limiting medical AI or the access to or use of medical certainties in order to stop them from exacerbating adverse selection—as well as the different reasons why these options fail to do so (created by the authors).

address adverse selection in the healthcare system, and not just counteract the factors that promote it, it might be most promising to address the problem at a structural level and think about how to reform the healthcare system (Albrecht, 2018)—and not make the mistake of focusing solely on regulating AI or new certainties.

In Germany there are longstanding political debates regarding the question whether and how to reform its current healthcare system. One prominent proposal is discussed under the label "Bürgerversicherung." It calls for a unified healthcare system in which all citizens participate and equally share the cost of their common disease risks, which would ensure the basic provision of medical services for all citizens and in which there is no possibility of opting out (Prasuhn and Wilke, 2021). While there would still be the option of obtaining additional private health insurance—thus retaining a degree of personal freedom of choice for citizens (Hussey and Anderson, 2003)—this proposal would dissolve the dual structure in which citizens can alternatively switch between public and private healthcare systems.

Since adverse selection is a fundamental challenge especially of dual healthcare systems (Prasuhn and Wilke, 2021), switching to a single-payer healthcare system would tackle adverse selection at the structural level. And if adverse selection is no longer possible, there is no longer the threat that using AI in medicine may exacerbate it. In a single payer system, it would be possible to apply AI to medicine, use its predictive capabilities to the maximum, and enjoy its benefits—better treatment and prevention options for patients, more predictive and safer planning and resource allocation options for healthcare systems, as well as lower insurance premiums for the individuals (Corea, 2019)—without having to worry about or having to take into consideration side-effects on incentives for adverse selection. These upsides remain robust across a variety of concrete configurations of the single payer system. One might, e.g., conceive of a more comprehensive approach to determining individual premiums which considers both risk and income of a person and might concurrently produce a surplus in efficiency. At the same time, some questions concerning the medical use of AI remain unaffected by switching to a single-payer system: how much certainty produced by AI is desirable in itself, how certainty about their future health affects peoples' self- and world perception, or whether in a single-payer system they can help to avoid treatment cost that seem superfluous through preventive behavior of the insured (Swedloff, 2014; Albrecht, 2018)?

In summary, we show how a single-payer healthcare system could enable the full use of AI in medicine and, conversely, how the use of AI in medicine could help make these healthcare systems more efficient and sustainable. Thus, without taking clear positions for or against such structural reforms, we provide some further arguments that might prove helpful in these discussions.

Scope of our results

While considering the medical use of AI and adverse selection, we focused mainly on Germany, its dual healthcare system and the legal situation there. Germany proved to be a good example, as the risk of adverse selection is particularly high, due to the reasons mentioned above.

However, our considerations are not limited to Germany. Rather, precisely due to the abstract nature of the concept of adverse selection, our considerations prove transferable to all contexts in which there is the possibility of individuals opting out of public healthcare systems and obtaining private health insurance exclusively—in short, to all countries with a dual private-public healthcare system. Besides Germany, these include Austria, France, Belgium, Luxemburg, and Japan (Rice, 2021; Schölkopf and Grimmeisen, 2021). However, these considerations also prove to be fundamental for the United States, where there are exclusively private health insurers and state welfare institutions—because, as evidence hints (Cameron and Trivedi, 1991), for people who are not part of the latter, their medical certainties might prove relevant for choosing private health insurance or no health insurance at all.

In this development, it is obvious that different AI systems will be established in different fields of medical application. Likewise, not all AI systems and the certainties they produce will be accessible right away. However, the technical framework strongly suggests that overall, and despite these differences in access and application, the level at which AI reduces uncertainties and produces certainties will increase.

Need for further empirical research

Further research on the effects of AI-based health prediction and new medical certainties on adverse selection in the healthcare system will have to elicit empirical data on the matter in order to realistically evaluate and specify these rather theoretical considerations.

Despite our paper being limited by not presenting empirical evidence, our considerations are in line with behavior that has been studied extensively and for a long time. Even though people have been found to exhibit social preferences (Kahneman et al., 2000; Fehr et al., 2008), and monetary incentives not being the only relevant factor in consideration (Andreoni, 1989; Regner, 2015), financial motives play a central role in decision-making. Also people tend to trust in the decision-making-ability of AI (Araujo et al., 2020). Which is why we assume, that people will also trust in the predictions given by AI.

There are empirical studies on related issues that may hint at initial empirical evidence supporting our considerations on adverse selection. Lünich and Starke (2021), e.g., investigated (in a not yet peer-reviewed study) to what extent personal financial benefits influenced persons' attitudes toward dual healthcare systems and their choice between public and private healthcare systems. They conclude that financial benefits, or the prospect of them, may have considerable influence on individual attitudes and decisions, as individuals often express their intent to switch to private health insurance if they expect to gain a financial benefit from it. Other studies have investigated the influence of fitness- and health-wearables on individual solidarity attitudes. They find people using wearables to be more likely to show less solidarity with other people and conclude that the digitization of health can be a challenge for public healthcare systems (Böning et al., 2019; Maier-Rigaud and Böning, 2020). Other studies have begun to empirically examine people's willingness to disclose private data in exchange for monetary benefits (Beresford et al., 2011; Schudy and Utikal, 2017). The above-mentioned studies and their results give no reason to doubt our theoretical considerations on medical certainty and adverse selection. On the contrary, they suggest that our considerations are valid—even if further studies on the connection between medical certainties and adverse selection are still needed.

Conclusion

The central question of our paper was whether it was possible to counteract adverse selection in the healthcare system—exacerbated by new, AI-generated medical certainties—by limiting or banning AI or its medical use, or by limiting access to medical certainties. After laying out how AI reduces existing medical uncertainties and generates new medical certainties by providing highly precise predictions of future medical conditions of individuals, we show how people can use this information to weigh the cost and benefits of switching from statutory to private health insurance and how this might lead to adverse selection and threaten public healthcare systems.

Finding existing regulatory instruments insufficient to mitigate these threats of adverse selection, we turned to the idea of banning or limiting AI and its medical use as well as limiting access to medical certainties as to counteract adverse selection. However, neither of the presented options provide adequate solutions, instead turned out to be either illiberal, paradox, impossible or unsustainable. We conclude that reinforced adverse selection as a result of AI-produced new medical certainties cannot be tackled on a symptomatic level as it is imminent in a dual healthcare system. Rather, the challenge calls for a more fundamental solution addressing the very structure of a healthcare system.

Our interdisciplinary study allows us to contribute to two current public debates. For one, we advance the discussion regarding regulatory guidance to balance promises and perils of AI application in medicine. At the same time, we provide a novel perspective on the debate regarding structural reforms of the German and comparable healthcare systems in response to the challenges it faces. In fact, our arguments posit that—given the technological revolution AI heralds—both debates must be considered simultaneously and in relation to each other in order to attain a comprehensive policy solution in either domain.

Author contributions

UvU, MT, DE, and CLvP contributed to the final paper through conceptualizing, writing, and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A novel technique for detecting sudden concept drift in healthcare data using multi-linear artificial intelligence techniques

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A financial market is a platform to produce data streams continuously and around 1. 145 Trillion MB of data per day. Estimation and the analysis of unknown or dynamic behaviors of these systems is one the challenging tasks. Analysis of these systems is very much essential to strengthen the environmental parameters to stabilize society activities. This can elevate the living style of society to the next level. In this connection, the proposed paper is trying to accommodate the financial data stream using the sliding window approach and random forest algorithm to provide a solution to handle concept drift in the financial market to stabilize the behavior of the system through drift estimation. The proposed approach provides promising results in terms of accuracy in detecting concept drift over the state of existing drift detection methods like one class drifts detection (OCDD), Adaptive Windowing ADWIN), and the Page-Hinckley test.

KEYWORDS

financial data, concept drift, sliding window, random forest, data stream

Introduction

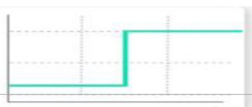
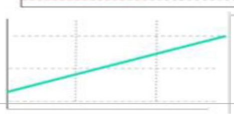
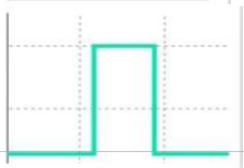
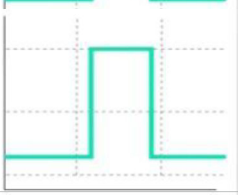
A financial market is a place for trading where the buyers and sellers make their transactions. The financial market includes stocks, bonds, derivatives, foreign exchange, and commodities. The data from the financial market is now available in a stream fashion and the analysis of the data has to be done at run time. The users in the financial market use these analyzed results for the purchase of goods or to sell their goods (Yoo et al., 2005). A financial market is very dynamic and there are a lot of fluctuations due to environmental factors and also due to some hidden factors (Fdez-Riverola et al., 2007). The AI model developed to predict the financial market will become obsolete due to changes in the financial market. These changes have to identify and have to be informed to users for their intelligent trading. Concept drift is the term used to describe the target changes involved in data (Gama et al., 2014). If there is concept drift, then the model accuracy will decrease and the model misclassifies the data. Whenever a concept drift occurs in the data then we need to identify and update the model with recent data. In our

TABLE 1 Summary of Drift Detection algorithms (Firas et al., 2022).

Category	Algorithm	Data retrieval	Test statistic calculation	Hypothesis test	Type of drift addressed
Online error rate based	DDM (Gama et al., 2004)	Landmark window	Online error rate	Distribution estimation	Sudden drift
	EDDM (Baena-Garc'ia et al., 2006)	Landmark window	Online error rate	Distribution estimation	Gradual drift
	Page-Hinckley (Qahtan et al., 2015)	Sliding window	Average value	Performance means	Sudden drift
	ADWIN (Cavalcante and Oliveira, 2015)	Auto cut W_{hist}, W_{new}	Error rate difference	Hoeffding bound	Sudden / gradual
	OCDD (Gozuacik, 2021)	Sliding window	Percentage of outlier	*Post hoc* Neymenvi test	Sudden / gradual

work, we will address how to handle concept drift by monitoring the performance of the classifier using a sliding window, random forest algorithm, and Hoeffding decision tree for anytime classification of financial data streams.

Concept drift can be categorized as (Gama et al., 2014):

Drift type	Behavior	Meaning
Sudden, Incremental, Gradual and Recurrent		
Sudden		Changes quickly from one concept to another concept
Incremental		Changes happens slowly over time
Gradual		Concept diminishing with new one
Recurrent		Concept repeats over time

Above Table 1 summarizes the different types error-based classification algorithms available to handle the different types of concept drift.

There are five ways to deal with concept drift (Das, 2021):

- **Online learning:** The learner is regularly updated as the model processes each sample. Online learning is the most popular method for reducing concept drift in real-world applications.
- **Periodically retrain:** The model is activated when the model's performance falls below a predetermined level or when the average confidence score between two windows of data shows a significant drift.
- **Periodically re-train on a representative sub-sample:** The sample selects sub-samples from a large population in such a way that a portion of the sub-sampling sample represents the entire population. If concept drift is discovered, employ an instance selection strategy that employs the same probability distribution as the original data. Humans change the labels in the current dataset to fine-tune the model.
- **Ensemble learning with model weighting:** Multiple models are grouped together, and the weighted average of the individual model outputs is used as the overall output.
- **Feature dropping**: Another method for dealing with concept drift is feature dropping. Using a single feature, multiple models are built at the same time, and where the AUC-ROC response is inadequate, those features are dropped.

Contribution of work

- A framework to detect concept drift in financial data streams by monitoring the performance of the model developed using a random forest algorithm and sliding window.
- Builds a decision tree incrementally using the Hoeffding tree for anytime classification and reset the tree once the drift is detected.
- Accuracy comparison of the proposed framework with one class drifts detection (OCDD), Page-Hinckley, and Adaptive Windowing (ADWIN) methods.
- Addresses the statistical significance of proposed framework using the Mcnemar's test.

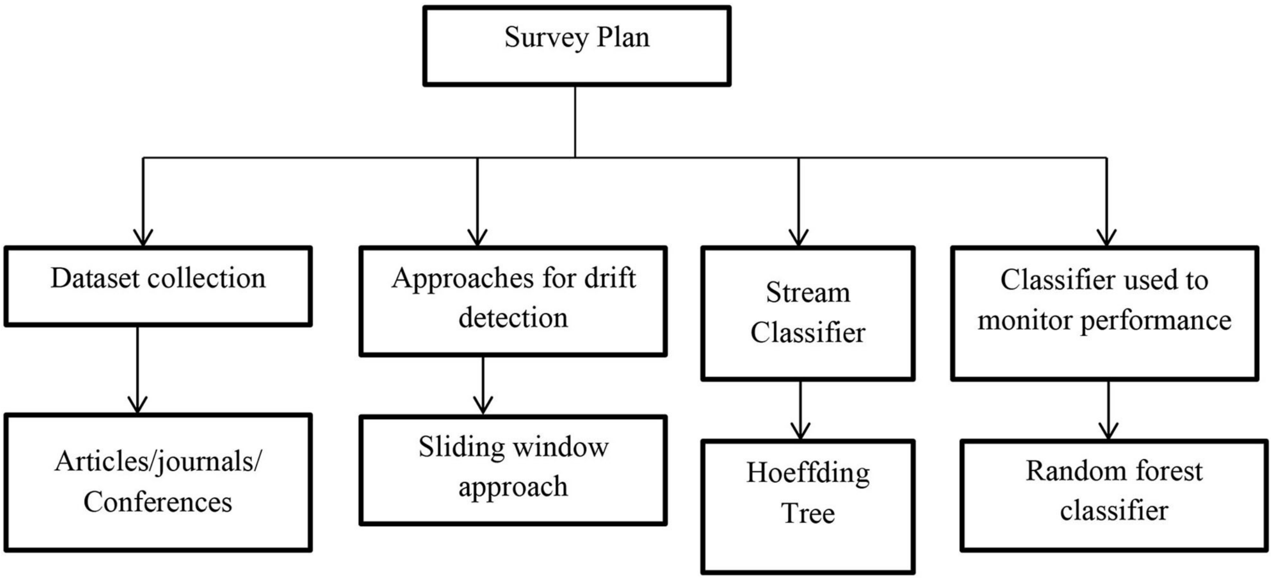


FIGURE 1
Literature methodology.

Organization of the paper

Chapter 1 gives the details about the introduction of our work. Chapter 2 gives the details about the literature methodology which will provide the essentials of our work. Chapter 3 addresses the background review of our topic which insights into the work carried out to detect concept drift in financial market data. Chapter 4 gives the process of our work i.e., the methodology we follow for the detection of concept drift. Chapter 5 provides the results of our work and comparison with the existing methods of drift detection. Chapter 6 gives the details about open research issues and research trends and chapter 7 details the future work to be done and chapter 8 gives the conclusion.

Literature methodology

The survey framework designed for the literature is as shown in Figure 1. The literature review process involves the following horizons. Table 2 describes the extensive literature work carried out by different authors and also mentioned the limitations of their work.

- Data collection for financial market data.
- Data collection for sliding window and random forest classifier.
- Stream classifier for incremental tree building.

Background review

Methodology

As shown in Figure 2, the data blocks are read to the model in a streaming fashion [4] and the random forest algorithm is used to develop the AI model and the performance of the model is monitored through classification metrics. If the accuracy of the model is less than the threshold then the model is rebuilt over the new data. We read each instance in the window and start to build the Hoeffding tree incrementally using the Hoeffding stream classifier. Once the data in the window is full the window is subjected to a random forest algorithm to monitor the performance of the model. If the performance of the classifier is below the threshold value then concept drift is signaled and the current tree builds incrementally used for making decisions will be discarded and in the window, a new space will be made to fill out the new samples to reflect the current distribution.

Algorithm

Step 1: Read data incrementally into the defined window size until the window becomes full.

Step 2: Train the model with the current window data using the Random forest algorithm and measure the performance of the model. If the performance of the model is less than the defined threshold then signal drift and go to step 3 else go to step 4.

TABLE 2 Literature.

Author	Title of the paper	Contributions	Limitations
Gustavo H. F. M. Oliveira	Time Series Forecasting in the Presence of Concept Drift: A PSO-based Approach (Oliveira et al., 2017)	• Proposes Particle Swarm Optimization method to detect concept drift in time series financial data. • The proposed method is robust to false positive drift while maintaining low error rate during forecasting. • The experiment was conducted on four artificial datasets and three real time datasets from Dow Jones, NASDAQ and Yahoo finance. • The proposed method detects concept drift well compared to the state of the art methods like DDM, ECDD and FEDD.	• Proposed method based on swarm behavior (IDPSO-ELM-B) did not yield a good detection curve. • The methods ELMECDD and ELM-DDM monitor the error only for one model.
Bruno Silva	Applying Neural Networks for Concept Drift Detection in Financial Markets (Bruno and Nuno, 2012)	• Proposed a framework using neural networks to monitor the interday changes in financial stock market over the last 10 years of Dow Jones Industrial Average index (DJI). • The method comprises two phases i.e. online data aggregation using ART network and monitor error rate to detect concept drift using Average Quantization error. • The proposed method addresses gradual and abrupt drift in stock market data.	• The framework does not mention Intraday trading in financial stock market data streams.
Filippo Neri	Domain Specific Concept Drift Detectors for Predicting Financial Time Series (Filippo, 2021)	• Proposed three concept detectors myTanDD which uses angle between tangent to the data, MINPS uses data mean and minimum standard deviation of all data points, and mySD uses standard deviation to detect concept drift for financial time series data. • Data is collected in a sliding window to calculate the statistics and make a decision about concept drift. Hyper parameter tuning is considered to increase the performance of the proposed classifiers.	• Study of Hyper parameters tuning can impact the systems performance.
Hanen Borchani	Modeling Concept Drift: A Probabilistic Graphical Model Based Approach (Hanen, 2015)	• Propose a framework, based on probabilistic graphical models, that explicitly represents concept drift using latent variables. Data from a European bank from the period of April 2007 to March 2014 is considered. The proposed model finds the different trends in the economic climate and analyzed policies implemented by the BCC bank. The model finds the interesting concept drift information of streaming financial data and compared with other non-streaming techniques.	• Only one latent variable is used for modeling concept drift
Rodolfo C. Cavalcante	An Approach to Handle Concept Drift in Financial Time Series Based on Extreme Learning Machines and Explicit Drift Detection (Rodolfo, 2015)	• Proposed online sequential extreme learning machines (OS-ELM) with explicit drift detection algorithms to detect concept drift. It updates the model during the presence of concept drift. The proposed algorithm gives equivalent accuracy in forecasting the time series financial data and takes less time to detect the drift.	• During the negotiation in a real-world market, the intelligent trading system should consider concept drift.
J. Gama	Drift Detection Method (DDM) (Gama et al., 2004)	• Monitors the number of errors for detecting concept drift. • It has two levels to signal drift, warning and drift level. • Detects sudden drift only.	• Detection rate is low for different types of drift. • It monitors the error rate of the classifier.
Baena-Garcia	Early Drift Detection Method (EDDM) (Baena-Garc'ia et al., 2006)	• Early drift detection method (EDDM) based on the distance between the classification errors. • The early drift detection algorithm is able to detect the concept drift. When the gradual variations in the dataset are present then there is a chance of early detection.	• It uses two thresholds to warn and detect drift. • It monitors the error rate of the classifier.

(Continued)

TABLE 2 Continued

Author	Title of the paper	Contributions	Limitations
Bifet	Adaptive Windowing (ADWIN) (Cavalcante and Oliveira, 2015)	• Proposed Adaptive-windowing (ADWIN) in which the window capacity is decided entirely by the rate of change seen in the data contained inside the window in the adaptive windowing approach. Here, a combination of NB and ADWIN supervises the error rate generated by the model and also makes the decision that the sample needs to be altered or not.	• ADWIN uses two sub-windows and compares changes in two sub windows. • It takes more computational time for deciding the sub window sizes.
A. A. Qahtan	Page-Hinckley Test (PHT) (Qahtan et al., 2015)	• Page hinckley test(PHT) employs statistical variation detection is employed to obtain the clusters for the data for detecting the drifts. For the model learning the DDM is employed and to detect the variation in the signal the PHT is used. • To detect the variation a continuous and a thorough examination is performed in PHT. By performing the average of the variations and distributions the concept drift can be detected.	• It uses two hypothesis tests to monitor the change in hypothesis to check for increase or decrease.
O. Gozuacik	One Class Drift Detection (OCDD) (Gozuacik, 2021)	• Implicit algorithm termed One-Class Drift Detector (OCDD) employs a one-class learner SVM and a window that slides to detect drift. • The classifier is trained to distinguish between the old and new instances and evaluate, if they are comparable. • If true, then indicates a drift depending on the rate of abnormality (outlier percentage) identified in the sliding window.	• Comparison of accuracy for the model by employing with different svm kernels. • Dataset is numerical in nature.
Tatiana Escovedo, Adriano Koshiyama, Andre Abs da Cruz, Marley Vellasco	DetectA: Abrupt Concept Drift Detection in Non-stationary Environments (Tatiana et al., 2018)	• DetectA is a concept drift detection method created for sudden concept drift detection. The primary innovation of this method is that it is proactive, as contrast to other drift detection approaches, which only identify concept drifts after they have already occurred. • A method for producing datasets with predefined sudden drifts has been suggested. In order to understand the degree of each parameter's influence on DetectA's ultimate performance, • A process based on differences in the amount of attributes, patterns, and imbalance rates between classes was used. • The detector is effective and appropriate for high-dimensional datasets, blocks of medium size, any amount of drifts, and class imbalance.	Clustering evaluation is not done using the metrics
Osama A.Mehdi, Eric Pardede, Nawfal Ali, Jinli Cao	Fast Reaction to Sudden Concept Drift in the Absence of Class Labels (Osama et al., 2020)	• A brand-new concept drift detector dubbed DMDDM-S that employs the PH test along with its computations to alter the disagreement measure. To determine the diversity of classifier responses in response to changing incoming data, DMDDM-S is proposed. • DMDDM-S uses the fading factor to track the diversity of a pair of classifiers instead of keeping track of the error estimates. • In comparison to the current methods, DMDDM-S identifies drifts with a smaller delay, less detection runtime, and less memory use.	The model was developed for semi supervised environment.

Step 3: If there is a drift in the window data then remove the w* ρ samples completely from the window and go to step 1.

Step 4: If there is no drift then remove w*(1- ρ) data samples from the window and go to step 1.

Step 5: If there are no samples remaining from the incoming data source then go to step 6.

Step 6: Exit.

Pseudo code

```
Algorithm-: Concept Drift Detector using Sequential analysis
Concept Drift Detector (d, w, r, t):
// d: Data Stream; w: window size; ρ: percentage of new data;
t: threshold
Window size S = (old data size + new data size)
Stream classifier SC = Hoeffding Tree Classifier
Drift Detection classifier DC = Random Forest algorithm
for each instance in d do
| Check IsEmpty(S)
| if Yes then
| | add instance X to window S
| | Train model SC
| else
| | |S| = |T| // Combine data with class labels
| | target = old for O [1, w]
| | target = new for N [w+1, end]
| | Train target with DC
| | Measure the performance metrics
| | Check Drift (DC, T)
| | if Yes then
| | | Shift (w* ρ) old data from the window S
| | | Reset and Retrain SC
| | else
| | | Shift w*(1- ρ) of old data w from the window S
| | | and Train model SC
| | end
| end
end
IsEmpty(S):
window index < window size
Drift (DC,T):
if AUC score and f1 score ≥ 0.7 then
| drift = No
else
| drift = Yes
end
```

Results and discussions

Dataset description

The dataset characteristics is presented in Table 3. The data is collected weekly from the poll done by the American association of individual investors and the dataset contains information from January 1st, 2003 to December 31st' 2020 from three different countries China, India, and UAE. The dataset contains the description of the US sentiment investors, Measure of Variability (spread) and US returns collected weekly, social and cultural development indicators like Human development, Gross development and Population growth (yearly), and other Sectors–Value Added (VA) as % GDP in achieving UN SDG 3 (Health and Wellbeing) & SDG 8 (Growth & Economic Development) like Human Development Index (HDI), Current Health Expenditure (CHE) as a percentage of GDP, and per capita, health expenditure in constant US$ are all factors in the health sector, Macro-Economic factors like risk rate, foreign direct investment, GDP (annual growth) and Inflation and also includes economic crisis and pandemic events as shown in Figure 3.

The classification task is to tell whether the country (China, India, and UAE) is going to retain their investors every week. (1 - Yes and 0 - No) as shown in Figure 4. Table 3

TABLE 3 Dataset features overview [18-23].

Attribute description	Name of the attributes
US sentiment	Bullish, neutral, bearish, 8-week BMA
Measure of variability	Spread
US Returns	Market return for US
Human development indicator	Human development index-HDI
Gross national income	Per capita CHE $, CHE %GDP
Population growth annual %	POP-G annual %
Health sector - nutrition	Anemia
Technology sector	INTERNET%
GDP - industry sector	Industry VA-% GDP
Manufacturing sector	MFG-VA%GDP
Services sector	SER-VA%GDP
Agriculture, fishery, forestry (AFF) Sectors	AFF VA-%GDP
Peer reviewed journals	PRJ-R&D
Sector - entrepreneurs	SELF EMP-T%, SELF EMP-M%, SELF EMP-F%
Stocks traded value (%GDP)	STOCKS-TRADED VALUE (%GDP)
Stocks traded turnover domestic (%)	STOCKS-TRADED-TO-D (%)
Real interest rate%	Real Int. rate%
Foreign direct investment	FDI NI%GDP
GDP-annual growth	GDP-AG%
Inflation - annual %	INF-A%
Economic crises (EC) and pandemic event (PE)	EC-PE CODE

10.3389/frai.2022.950659

TABLE 4 Classification report for Figure 5A TP = 116, FN = 64, FP = 69, TN = 76.

	Precision	Recall	F1-score	Support
0	0.54	0.52	0.53	145
1	0.63	0.64	0.64	180
Accuracy			0.59	325
Macro avg	0.58	0.58	0.58	325
Weighted avg	0.59	0.59	0.59	325

TABLE 5 Classification report for Figure 5B TP = 124, FN = 87, FP = 76, TN = 113.

	Precision	Recall	F1-score	Support
0	0.56	0.60	0.58	189
1	0.62	0.59	0.60	211
Accuracy			0.59	400
Macro avg	0.59	0.59	0.59	400
Weighted avg	0.59	0.59	0.59	400

TABLE 6 Classification report for Figure 5C TP = 129, FN = 116, FP = 83, TN = 147.

	Precision	Recall	F1-score	Support
0	0.56	0.64	0.60	230
1	0.61	0.53	0.56	245
Accuracy			0.58	475
Macro avg	0.58	0.58	0.58	475
Weighted avg	0.58	0.58	0.58	475

describes the Dataset features[1,2,3,4,5,6,7] used by the authors for their implementation.

1 "Multiflow," scikit, June 17, 2020, https://scikit-multiflow.github.io/.

2 Assets.kpmg. https://assets.kpmg/content/dam/kpmg/ae/pdf-2020/09/uae-healthcare-perspectives.pdf.

3 "Investment Opportunities in China's Healthcare Sector after COVID-19." China Briefing News, 26 Mar. 2020, https://www.china-briefing.com/news/investment-opportunities-chinas-healthcare-sector-aftercovid-19/.

4 "China Stock Market - Shanghai Composite Index." MacroTrends, https://www.macrotrends.net/2592/shanghai-composite-index-china-stock-market-chart-data.

5 "Healthcare Industry in India, Indian Healthcare Sector, I..." Industry in India, Indian Healthcare Sector, Invest..., https://www.investindia.gov.in/sector/healthcare.

6 Healthcare July 2019 - IBEF. https://www.ibef.org/download/Healthcare-July-2019.pdf.

7 "Dubai: Global Healthcare Destination." Medical Toursim, https://www.medicaltourism.com/destinations/dubai.

Classification metrics

		Predicted values	
		0	1
Actual values	0	TN	FN
	1	FP	TP

TP = True Positive, FP = False Positive
TN = True Negative, FN = False Negative
Accuracy = TP + TN / TP + TN + FP + FN
Precision = TP / TP + FP
Recall = TP / TP + FN
F1-score = 2*precision*Recall / Precision + Recall
Macro-avg is the mean average of the F1 score of all classes.
Macro-avg = (F1 score of class 0 + F1 score of class 1) / 2.

Tables 4–6 describes the accuracy metrics for different data blocks. The weighted-average is calculated by taking the mean of all per-class F1 scores while considering each class's support.

Example: Classification report for Figure 5A TP = 116, FN = 64, FP = 69, TN = 76

Macro Average = (F1 score of+ class 0 + F1 score of class 1) / 2.

= (0.53 +0.64) / 2 = 0.58

Weighted Average = Mean of all per-class F1 scores while considering each class's support.

= (0.53 * (145/325) + 0.64 * (180 /325))

= 0.59

Similar to Figure 5A, the calculation for macro average and weighted average will be done for 5B and C.

Table 7 displays the comparison bar graph between the proposed concept drift detection framework results and OCDD method results for different hyperparameter values like window size, threshold, and percentage of data in the sliding window. In comparison, the proposed framework gives good results for the accuracy metric over OCDD for smaller window sizes i.e. from window sizes 25 to 250.

$$[w = 250, rho = 0.1, T = 0.9][w = 250, rho = 0.2, T = 0.8]$$
$$[w = 250, rho = 0.3,\ T = 0.7]$$

The above Figures 6A–C diagrams depict the accuracy graph of the proposed concept drift detection technique for different hyperparameter values. The x-axis displays the percentage of data and the y-axis displays the accuracy. Whenever the accuracy of the model declines below 0.7 then concept drift will be signaled and the percentage of data will be added to the sliding window.

The above Figures 7A–C diagrams depict the accuracy graph of one class drift detection technique for different

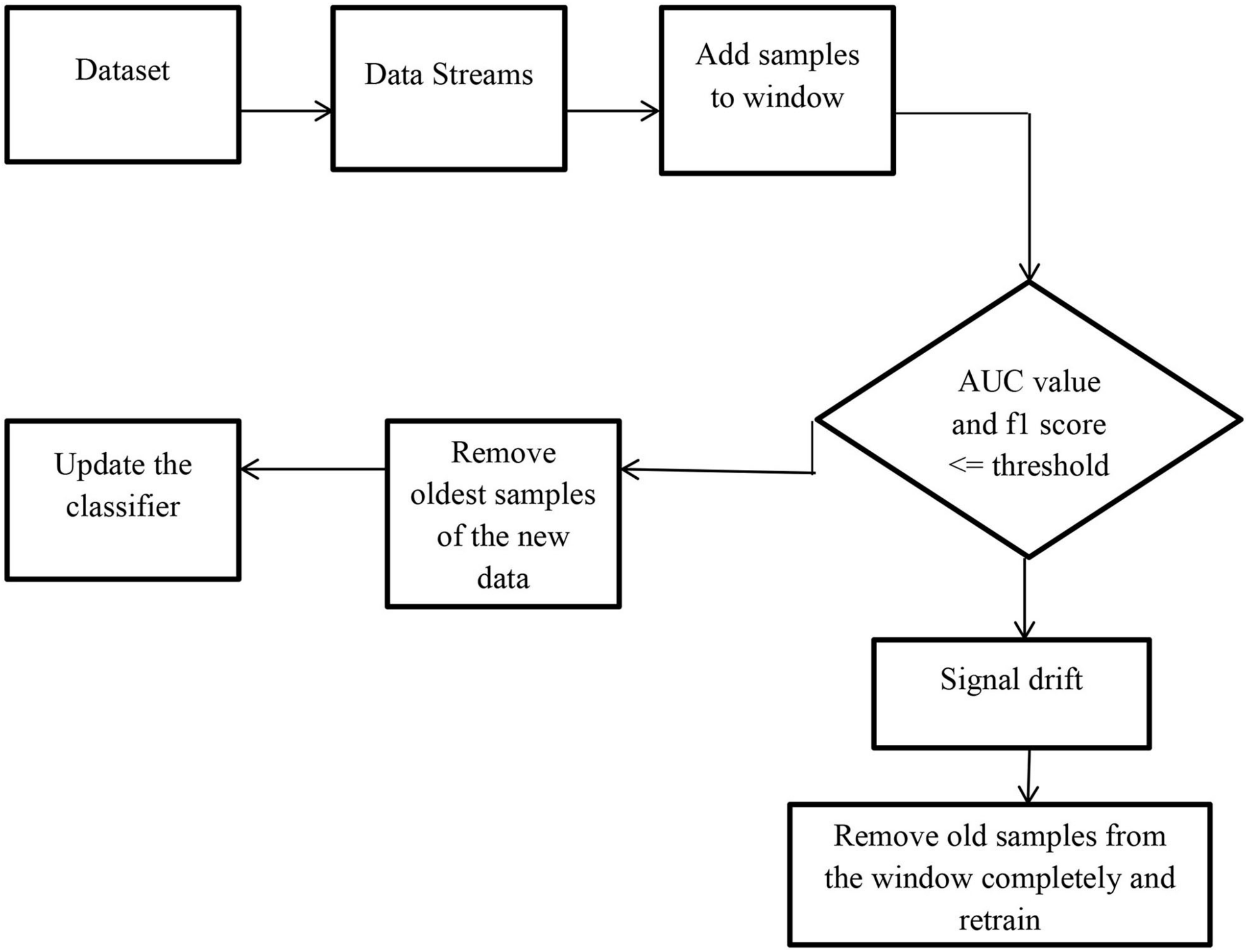


FIGURE 2
Framework to detect sudden concept drift in data streams.

hyperparameter values. The x-axis displays the percentage of data and the y-axis displays the accuracy.

Figure 8 depicts the comparison of the proposed concept drift detector technique with the Page-Hinkley method and window-based method ADWIN. In comparison, the proposed method outstands in accuracy for different values of window size.

A random forest algorithm is used in the proposed solution to develop the AI model and to monitor the performance. We have tuned the tree depth to create an appropriate balance between bias and variance to get the optimum generalization performance.

The following Tables 8–10 describe the tuning of the tree depth for the window size w =250 for threshold ε {0.7, 0.8, 0.9} and percentage of new data $(\rho)\varepsilon$ {0.3, 0.2, 0.1}

Tuning the hyperparameters of the random forest like depth of tree ε {05, 10}, a number of estimators ε {100, 200}, the minimum number of samples in leaf node ε {50,100}, we found that for window size 250 the classification metrics will provide the promising results for threshold value = 0.7 and percentage of new data = 0.3 compared to different values of threshold and percentage of new data as shown in Figure 9.

We use Mcnemar's test to perform a significance test for classification to compare the accuracy of our proposed concept drift technique with the accuracy of the OCDD technique. The McNemar's test is a paired nonparametric or distribution-free statistical hypothesis test. It is used to test the significance of two classifiers over a single dataset. In the Mcnemar's test, the null hypothesis we formulate is that the performance of two models is the same, and in the alternative hypothesis that the performance of two models is different.

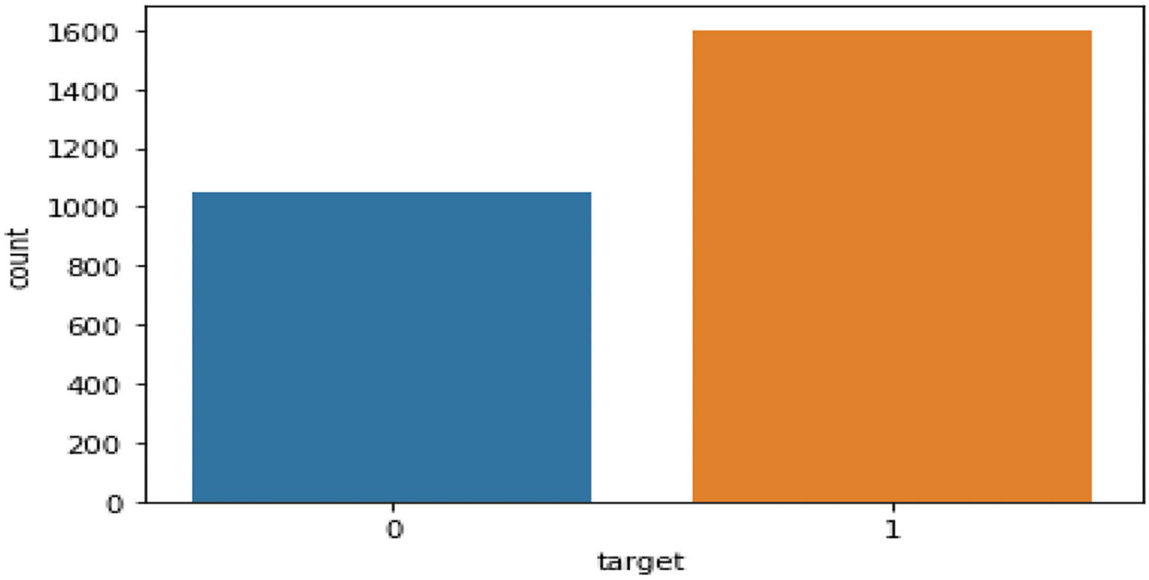


FIGURE 3
Data distribution of target variable.

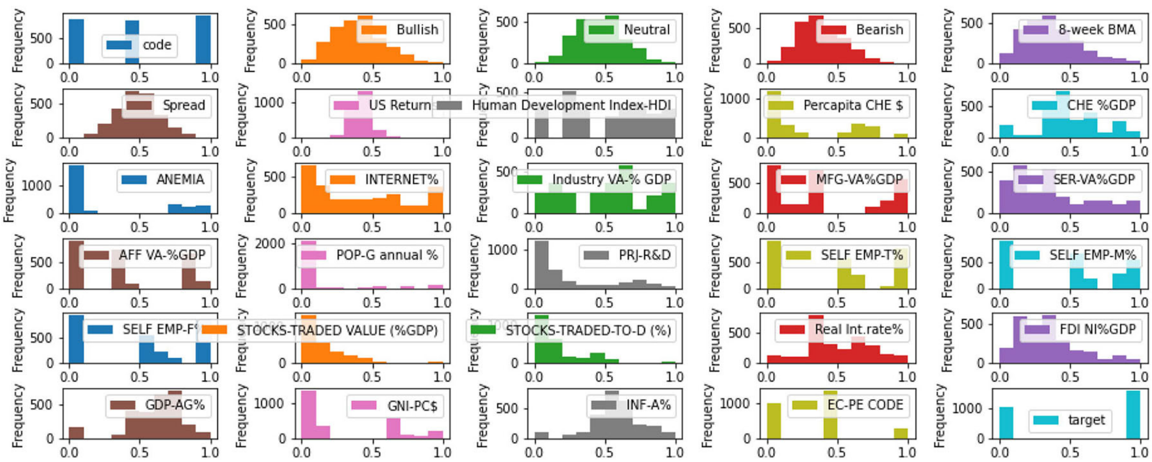


FIGURE 4
Data distribution of features.

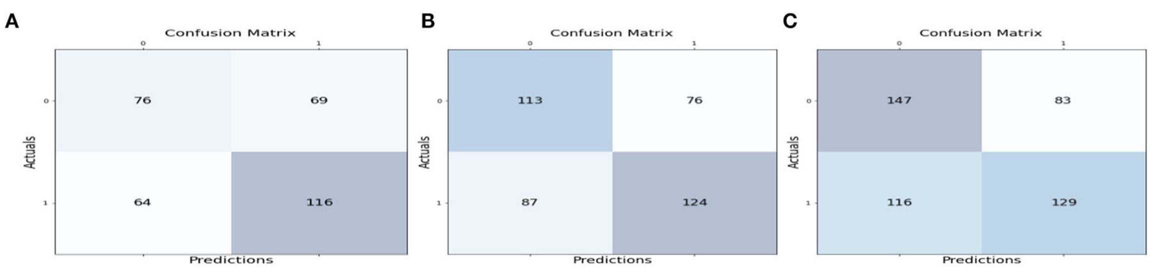
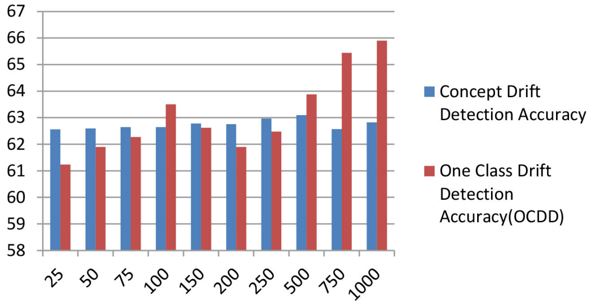


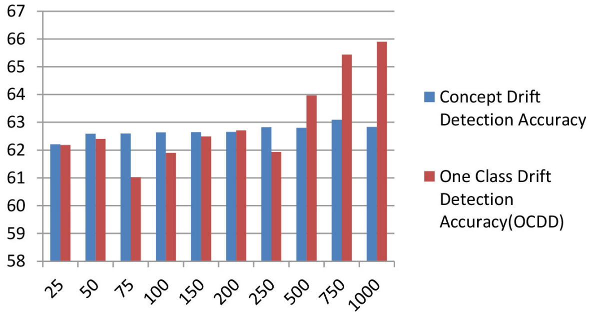
FIGURE 5
Confusion matrix values for the first three streaming blocks of data.

TABLE 7 Accuracy comparison of proposed concept drift detection technique with once class drift detection (OCDD) for different values of hyperparameters like window size, percentage of new data, and threshold.

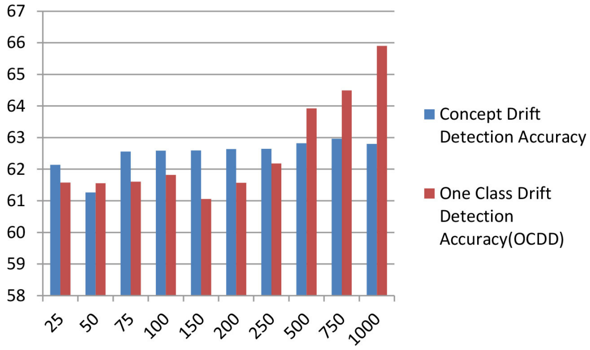
Threshold = 0.7, Percentage of new data = 0.3



Threshold = 0.8, Percentage of new data = 0.2



Threshold = 0.9, Percentage of new data = 0.1



x-axis represents window size and the y-axis represents accuracy in percentage.

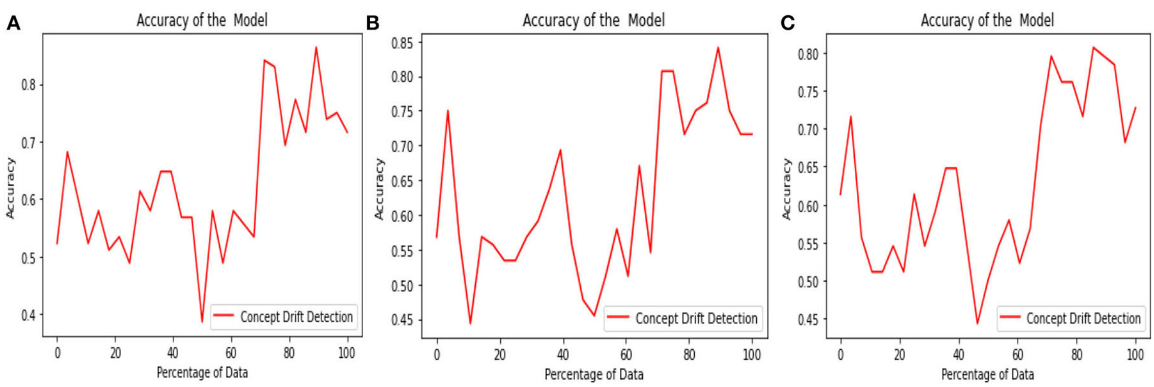


FIGURE 6
Accuracy Graph of proposed concept drift detection technique for window size =250, percentage of new data = [0.1, 0.2, and 0.3] and threshold = [0.9, 0.8, and 0.7].

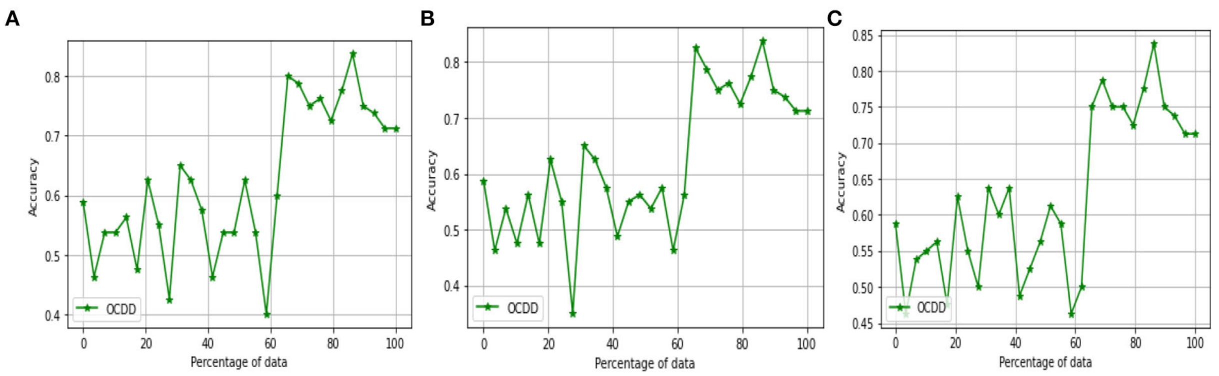


FIGURE 7
Accuracy Graph of one class drift detection technique [OCDD] for window size =250, percentage of new data = [0.1, 0.2, and 0.3] and threshold = [0.9, 0.8, and 0.7].

The McNemar's test[8] statistic ("chi-squared") can be computed as follows

$$\chi^2 = \frac{(b-c)^2}{(b+c)} - - - - - - - - \rightarrow (Equation\ 1)$$

With one degree of freedom and an alpha value of 0.05, we compute the p-value for some blocks in the below table.

Streaming blocks of data		p	Significance
Block 1	Proposed method v/s OCDD	0.7287	True
Block 2	Proposed method v/s OCDD	0.4335	True
Block 3	Proposed method v/s OCDD	0.8180	True

Open research issues and research trends

Research issues

The following are some of the research issues that can be addressed in the future:

- Handling outliers and class imbalance in data streams during concept drift detection.
- To design a single drift classifier that can address all types of drifts.
- The majority of methods rely too heavily on tracking the decline in learner accuracy. To have a stronger assumption on drift detection, a multiple hypothesis technique could be used in conjunction with other metrics being monitored.

8 http://rasbt.github.io/mlxtend/user_guide/evaluate/mcnemar/.

Research trends

- To create data streaming techniques that scale to massive deep learning networks and are effective across all domains.
- Conducting online learning by utilizing distributed streaming engines, such as Apache Spark, Apache Flink, Apache Storm, and others, will be a key trend when dealing with massive amounts of data.
- Traditional deep learning methods must make numerous passes through the data. How to create models for concept drift detection in data streams that simply perform one pass through the data without saving the data.
- Unsupervised methods for handling concept drift in the absence of class labels.

Future enhancement

The proposed work employs a framework for the detection of concept drift in financial data streams. The data employed in the framework for concept drift detection is numerical in nature and in the future can be worked on categorical data for concept drift detection. The framework is developed for sudden concept drift and can be used and analyzed for different types of drift. Multiple real-world and synthetic financial datasets can be considered for analyzing the results of the proposed

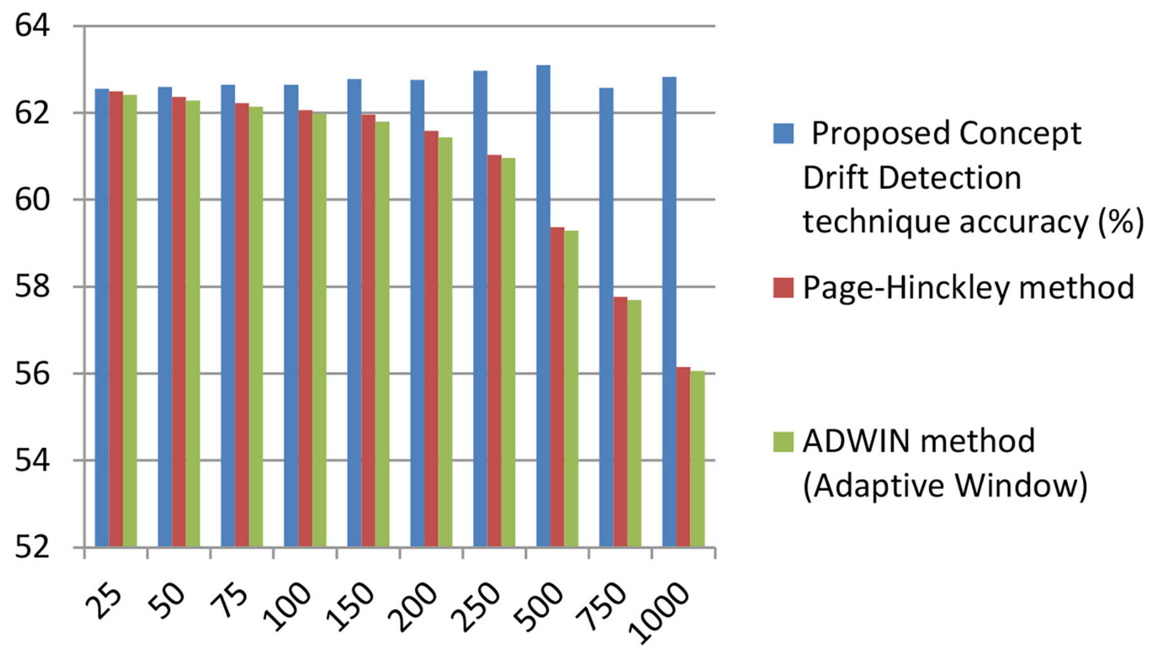


FIGURE 8
Accuracy comparison of proposed concept drift detector technique with Page –Hinckley, and ADWIN (adaptive window) method for varying window size. (x-axis represents window size and the y-axis represents accuracy).

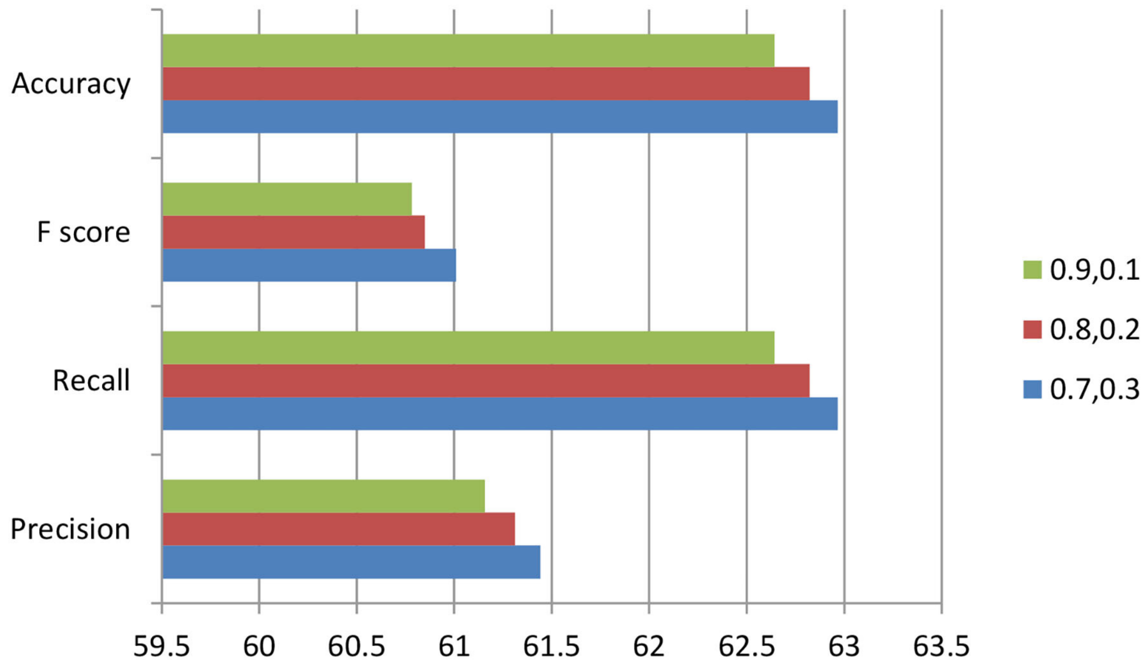


FIGURE 9
For Window Size =250, Threshold ∈ {0.9, 0.8, 0.7}, Percentage of new data ∈ {0.1, 0.2, and 0.3}.

TABLE 8 Window size = 250, Threshold = 0.7 Percentage of new data = 0.3.

Depth	Number of estimators	Minimum samples leaf	Maximum features	Precision	Recall	F score	Accuracy
05	100	50	Auto	61.4405	62.9658	61.0087	62.9658
10	100	50	Auto	61.4405	62.9658	61.0087	62.9658

TABLE 9 Window size = 250, Threshold = 0.8 Percentage of new data = 0.2.

Depth	Number of estimators	Minimum samples leaf	Maximum features	Precision	Recall	F score	Accuracy
05	100	50	Auto	61.3117	62.8220	60.8498	62.8220
10	100	50	Auto	61.3117	62.8220	60.8498	62.8220

TABLE 10 Window size = 250, Threshold = 0.9 Percentage of new data = 0.1.

Depth	Number of estimators	Minimum samples leaf	Maximum features	Precision	Recall	F score	Accuracy
05	100	50	Auto	61.1582	62.6428	60.7824	62.6428
10	100	50	Auto	61.1582	62.6428	60.7824	62.6428

framework. The time complexity of the model can be studied as a future scope.

Conclusion

The proposed framework uses a random forest algorithm to detect sudden concept drift by monitoring the performance of the classification metrics like f1 score and AUC value with different threshold values for financial data streams. The proposed work detects sudden concept drift well for smaller window sizes and the results are compared with OCDD, Page-Hinckley, and ADWIN methods.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

MA and CRN made substantial contribution to conception and design and acquisition of data. MA and SBR involved in analysis and interpretation of data. MA, CRN, and SBR drafted the article. MSAR contributed during the entire revision by answering to the reviewer comments and analysis of the proposed model results since from the first review process. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frai.2022.950659/full#supplementary-material

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The role of artificial intelligence based systems for cost optimization in colorectal cancer prevention programs

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Colorectal Cancer (CRC) has seen a dramatic increase in incidence globally. In 2019, colorectal cancer accounted for 1.15 million deaths and 24.28 million disability-adjusted life-years (DALYs) worldwide. In India, the annual incidence rates (AARs) for colon cancer was 4.4 per 100,000. There has been a steady rise in the prevalence of CRC in India which may be attributed to urbanization, mass migration of population, westernization of diet and lifestyle practices and a rise of obesity and metabolic risk factors that place the population at a higher risk of CRC. Moreoever, CRC in India differs from that described in the Western countries, with a higher proportion of young patients and more patients presenting with an advanced stage. This may be due to poor access to specialized healthcare and socio-economic factors. Early identification of adenomatous colonic polyps, which are well-recognized pre-cancerous lesions, at the time of screening colonoscopy has been shown to be the most effective measure used for CRC prevention. However, colonic polyps are frequently missed during colonoscopy and moreover, these screening programs necessitate man-power, time and resources for processing resected polyps, that may hamper penetration and efficacy in mid- to low-income countries. In the last decade, there has been significant progress made in the automatic detection of colonic polyps by multiple AI-based systems. With the advent of better AI methodology, the focus has shifted from mere detection to accurate discrimination and diagnosis of colonic polyps. These systems, once validated, could usher in a new era in Colorectal Cancer (CRC) prevention programs which would center around "Leave *in-situ*" and "Resect and discard" strategies. These new strategies hinge around the specificity and accuracy of AI based systems in correctly identifying the pathological diagnosis of the polyps, thereby providing the endoscopist with real-time information in order to make a clinical decision of either leaving the lesion *in-situ* (mucosal polyps) or resecting and discarding the polyp (hyperplastic polyps). The major advantage of employing these strategies would be in cost optimization of CRC prevention programs while ensuring good clinical outcomes. The adoption of these AI-based systems in the national cancer prevention program of India in accordance with the mandate to increase technology integration could prove to be cost-effective and enable implementation of CRC prevention programs at the population level. This level of penetration could potentially reduce the incidence of CRC and improve patient survival by enabling early diagnosis and treatment. In this review, we will highlight key advancements made in the field of AI in the identification of polyps during colonoscopy and explore the role of AI based systems in cost optimization during the universal implementation of CRC prevention programs in the context of mid-income countries like India.

KEYWORDS

artificial intelligence, colorectal (colon) cancer, colonoscopy, screening, cost-benefit, cost-effect analysis

Introduction

Artificial intelligence has seamlessly integrated with Gastrointestinal endoscopy by enhancing the human capabilities combined with the infallible precision of machines. Innovations in Machine learning (ML) and computer aided detection (CADe)/computer aided diagnostic systems (CADx) have opened new paradigms that have re-defined our understanding of the world of endoscopy. Advanced imaging techniques such as Narrow Band Imaging (NBI) and pre-processing techniques like chromo-endoscopy, have provided AI-based programs a platform to create a significant impact in diagnostic endoscopy. Although AI has been widely used as a tool for better detection of pathology during the endoscopy, the shift of AI based systems to assume the role of "characterization" of the lesion in addition to locating the lesion is an exciting prospect that can have far-reaching implications in the field of endoscopy (Van Der Sommen et al., 2020). This has been mainly due to a rapid improvement in computing power, which has enabled these AI-based systems to open up novel strategies that can potentially improve cost-effectiveness and transform the endoscope into a powerful tool for preventive programs at the community level.

Colorectal cancer (CRC) is a leading cause of death with a rising incidence especially in younger age-groups, both in western countries as well as many Asian countries in the recent past (Aran et al., 2016; Deng, 2017; Mattiuzzi et al., 2019; Onyoh et al., 2019; Awedew et al., 2022; Shakuntala et al., 2022). According to GLOBOCAN 2020 data, Colorectal Cancer is the second most deadly (9.4% of total deaths) and the third most diagnosed (10.0% of total malignancies) cancer globally. Although the frequency remains higher in highly developed countries, the trend has recently stabilized or even decreased (Sung et al., 2021). However, an increase in CRC incidence and mortality has been found in medium and high human development index (HDI) countries (Deng, 2017; Veettil et al., 2017; Onyoh et al., 2019). This can be partially attributed to rapid adoption of "western" type of diets and sedentary lifestyle practices in these regions. Japan and Thailand are witnessing rapid increases in colorectal cancer incidence (Khuhaprema and Srivatanakul, 2008) and CRC incidence has been showing a steady rise in Iran over the last three decades (Dolatkhah et al., 2015). India is another country which has shown a steady rise in CRC incidence owing to changing dietary and lifestyle practices (Shakuntala et al., 2022). The treatment outcome for CRC is heavily dependent on stage at which diagnosis is established. Early-stage tumors carry a favorable prognosis with 90% survival at 5 years. However, late-stage cancers have a poor prognosis highlighting the need for screening programs that can enable early diagnosis (Färkkilä et al., 2015; Marley and Nan, 2016; Arnold et al., 2017).

CRC places a significant burden in terms of morbidity, mortality, and economic cost (Jansman et al., 2007). Previous studies conducted in high-income countries showed that the CRC imposes a high financial cost on societies and accounts for 10% of the overall economic burden of cancer. In fact, estimated economic burden to the US, England, and Korea was \$14.14 billion, £542 million, and \$810 million, respectively, in 2010 (Tangka et al., 2008). Essential components of the economic burden of CRC include direct medical care, nonmedical costs and productivity losses among patients and caregivers (Färkkilä et al., 2015). The healthcare expenses that are incurred by the patient and his/her family are termed out-of-pocket (OOP) expenses. Productivity costs are significant as both, the patient and his/her caregiver may have to reduce their working hours, which then results in loss of income. Moreover, self-employed patients and their caregiver(s) may occasionally have to close their business (Kolligs, 2016).

These financial considerations have been magnified by the increasing incidence of CRC in low- and middle income countries due to the growth in the aging population and rapidly changing lifestyles. Late diagnosis of CRC leads to a bad prognosis and further loss of productivity of cancer patients and caregivers thereby leading to a significant impact on the family income with downstream effects on the society as a whole (Kolligs, 2016).

In the last decade, there has been increased focus on assessing the financial burden among cancer patients and their families. For instance, subjective financial difficulty in colon cancer patients was assessed in the USA, and it was reported that 38 % of cancer patients have at least one management-related economic burden (Kolligs, 2016). One of the most cost-effective strategies of CRC management, is prevention programs using procedures like colonoscopy/sigmoidoscopy. CRC screening programs have been established in many western countries and have shown significant impact on cancer burden as well as cost-effectiveness. The objective of this paper to review the current status of Computer aided detection and diagnostic systems in CRC screening programs as viewed through the prism of financial implications on healthcare management. To that end, we will first outline the financial aspects and clinical impact of CRC screening programs in general. This will be followed by an analysis of available literature on the efficacy of CADe and CADx integration into the CRC screening programs. Finally, we will review the financial implications of these systems for CRC screening and chart a roadmap for the future of AI in CRC prevention and its potential impact on healthcare costs at the level of the individual as well as the healthcare system.

Clinical highlights, financial aspects and a critical appraisal of CRC screening programs

Most CRC develops from pre-existing adenomas which are pre-cancerous lesions (Leslie et al., 2002). Adenomas can be detected during a colonoscopic examination of the large bowel. These adenomas are resected during the colonoscopy thereby reducing the risk of malignant transformation to CRC (Corley et al., 2014), Therefore, Adenoma Detection Rate(ADR) is an important metric for quality assessment of CRC prevention programs. Increases in ADR (by even 1%) has shown significant reduction in the rate of interval colon cancer (by around 3%) (Corley et al., 2014). Screening for colonic polyps has been instrumental in reducing CRC burden in many countries. Guidelines for screening colonoscopy with the removal of colorectal polyps every 10 years from age 50 years have been implemented in many countries in Europe and North America. Apart from training requirements for colonoscopy, optimal visualization of polyps is an area that merits further attention. Factors that can interfere with visualization of polyps during colonoscopy include those that are hidden in mucosal folds, polyps which are subtle, diminutive or transiently visible (Wang et al., 2020a). Adequate training of endoscopists to adhere to international standards of withdrawal time, quality of bowel preparation and the use of scopes that have a wider viewing angle, can be potential avenues to address these issues (Mahmud et al., 2015). However, despite this, rates of missed adenomas can be as high as 26% for polyps <5 mm in size (van Rijn et al., 2006). Adenoma Missed Rates(AMR) can be as high as 5.4% even in the case of advanced adenomas >5 mm in size (Ahn et al., 2012). In this context, AI-based systems have an important role in improving accuracy and sensitivity of colonoscopic detection and diagnosis.

Relevant financial aspects of CRC screening programs

Screening for colorectal cancer (CRC) reduces mortality and improves the quality of life through earlier detection of precancerous polyps and thus more effective treatment of cancers. Overall costs of such programs go well-beyond the cost of the individual screening tests provided. They include expenditures to hire staff, establish contacts and partnerships with providers, develop databases and other mechanisms to maintain records and track patient outcomes, recruit patients, provide professional education, and establish medical advisory boards (Vahdatimanesh et al., 2017). Programs that provide screening services to underserved populations can incur high costs in outreach, patient education, and case management. The Centres for Disease Control and Prevention (CDC) established the Colorectal Cancer Screening Demonstration Program (CRCSDP) in 2005 to explore the feasibility of establishing a CRC screening program for the underserved U.S. population (see Figure 1).

The economic implications of colorectal cancer treatment are substantial. Factors associated with the cost of colon cancer treatment are stage of cancer, treatments that are done, places of treatment (private or public hospital), number of sessions and cycles of chemotherapy medicines used in the treatments, equipment used, and pre-colon cancer treatment (Kolligs, 2016), The treatment costs are mainly attributable to the early and terminal stages of the disease (i.e., surgery, hospitalization, chemo- and immunotherapy, and supportive care). Surgery is still the most effective treatment modality for colorectal cancer. The introduction of new chemo- and immunotherapeutics have also caused a continuing increase in treatment expenditures (Färkkilä et al., 2015; Kolligs, 2016).

The total costs to CRC include direct health care costs, informal care costs, and productivity losses. Costs of CRC are varied in various stages of the disease. Direct costs are expected to be high within 6 months of diagnosis because of operative intervention and hospitalization followed by palliative/rehabilitation care. Considering the treatment variability and intensity, India's colon cancer treatment cost varies from 1,085.82 to 9,147.52 USD. Different treatment options available for colon cancer in India are Surgery, chemotherapy, targeted therapy, and Immunotherapy, and the approximate cost is $9,147, $1,085, $4,118, and $9147, respectively (Marley and Nan, 2016) (see Table 1).

The financial burden of cancers treatment is especially severe in developing economies like India, often forcing

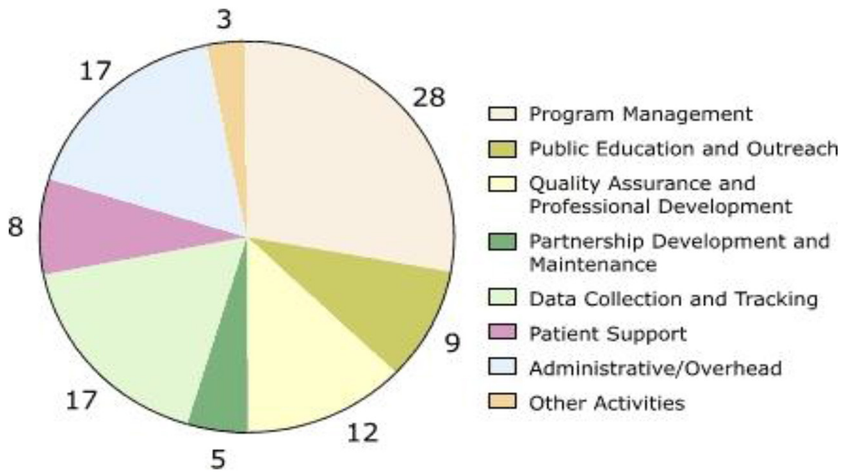

FIGURE 1
Percentage distribution of start-up costs, by activity, averaged across the five programs in the Colorectal Cancer Screening Demonstration Program, 2005–2006. Numbers do not add up to 100% due to rounding.

TABLE 1 Expected cost of tests and pre-colon cancer treatment in India.

Tests	Description
Health check-up	Physical examination and health check up with your doctor might cost around $8 (₹600)–$70 (₹5,000)
Fecal occult blood test (FOBT)	The price range of FOBT test ranges from $5 (₹300)–$8 (₹500)
Barium enema	Barium enema cost lies between $22 (₹1,540)–$42 (₹3,000)
Sigmoidoscopy	The cost of Sigmoidoscopy is from $150 (₹10,500)–$320 (₹22,400)
Virtual colonoscopy	The cost of virtual colonoscopy lies between $1,400(₹98,000)–$1750(₹1,22,500)
Colonoscopy	The approximate cost of colonoscopy lies between $2000(₹1,40,000)–$2,500(₹1,75,000)
Biopsy	The cost of biopsy lies between $429 (₹30,000)–$500 (₹35,000).

patients into insolvency (Mahal et al., 2013; Rahman et al., 2013). Hospital based studies done in India have shown that, on an average, a household spends USD 473.82 on cancer treatment. Since the average monthly income in the country in USD 422.18, strategies that can reduce the cancer burden, improve healthcare accessibility and manage the burgeoning costs of cancer treatment, could have a massive impact on cancer related financial burden in the country.

Are colorectal cancer screening programs cost-effective?

In general, there is evidence that improved preventive strategies (primary and secondary) and sustainable screening practices (test or procedure used to detect disease) could reduce the cancer- related mortality by ~60% (Colditz and Wei, 2012). In the context of CRC, the most effective way of prevention has been the large-scale deployment of screening colonoscopy among average to high-risk population. Screening colonoscopy with removal of colorectal polyps reduces colorectal cancer incidence and mortality (Wolf et al., 2018). The uptake for the screening program in USA has been ~60% (Shaukat et al., 2013; Brenner et al., 2014; Zorzi et al., 2015; Lin et al., 2016; de Moor et al., 2018). Screening colonoscopy is costly and resource-intensive. However, there is evidence to show that it is cost-effective owing to the savings related to cancer treatment. In a systematic review and meta-analysis of studies that employed screening colonoscopy and sigmoidoscopy for prevention of CRC, there was a 40–60% lower risk of incident CRC and mortality (Brenner et al., 2014). In a study by Shaukat et al., patients who underwent a screening colonoscopy were followed up over a period of 30 years. Screening reduced colorectal-cancer mortality [relative risk of 0.68 with annual screening and relative risk of 0.78 with biennial screening (two yearly)] over 30 years of follow-up. This sustained reduction in risk of cancer related mortality reflects the impact of polypectomy during the screening colonoscopy procedures (Shaukat et al., 2013).

An Italian study Senore et al. (2019) published in 2019 assessed the cost-effectiveness of CRC screening programs. Using data from the Piedmont program, a Markov model was constructed to simulate the cost of screening procedures performed and weighed against the benefit of screening. The simulated screening strategies were effective in reducing incident CRC by 10–17% and were also cost-effective (Incremental cost-effectiveness ratio <1,000 euros per life year saved) (Senore et al., 2019). Even among patients who had a screen detected CRC (SD-CRC) the short term and long term outcomes were found to be much better than non-screen detected CRC (Spolverato et al., 2021). In Austria, decision-analytic cohort simulation model for colorectal adenoma and cancer with a lifelong time horizon was developed to assess the cost-effectiveness of CRC screening. Screening colonoscopy was the most effective strategy and was also found to be cost saving as compared to no screening using this model (Jahn et al., 2019).

These findings establish the pivotal role played by colonoscopy screening programs in reducing the disease burden as well as financial burden of CRC. In addition, they also establish the cost-effectiveness of colonoscopy screening in reducing cancer incidence, cancer treatment related costs and hospital admissions. However, there are inherent drawbacks to current colonoscopy protocols that can have significant downstream effects, both in terms of efficacy as well as financial ramifications.

In the subsequent sections of this article, we will review the status of artificial intelligence in CRC screening programs along with future directions for AI integrated CRC screening tools. We will review existing data on cost-effectiveness of AI-integrated solutions and propose a roadmap for optimization of CRC screening programs in the future.

Current status of AI based systems in colonoscopy screening programs for CRC and its financial implications

The initial application of AI in endoscopy was limited to "edge detection" by identifying sharp changes in brightness, texture and "region growing" by a group of pixels of similar properties. This was useful for lesions with edges that were undetectable during standard endoscopy (Attardo et al., 2020). With the advent of advanced endoscopic imaging, subsequent Deep Neural Networks(DNN) systems could make use of additional features like texture, color, brightness and temporal factors with a high level of precision (Sánchez-Peralta et al., 2020). Subsequently, novel ML techniques were applied that could take advantage of vast datasets along with standardized image processing, to enable complex functions like accurate polyp location and classification (Yamada et al., 2019). Since, then, multiple systems have been developed that have shown improved results and accuracy (Wang et al., 2015; Misawa et al., 2016; Chen et al., 2018; Byrne et al., 2019).

Various Computer Aided Detection (CADe) systems have been applied for real-time colonoscopic detection of polyps. They have demonstrated a good accuracy for polyp detection, especially for polyps <1 cm. These systems have supplemented the endoscopist's ability to locate lesions that are obscured by debris, or poorly visualized due to specular reflections (Bernal et al., 2017). One of the first few CADe systems developed by Wang et al. was validated in a large multi-centric trial. The CADe system significantly increased mean number of adenomas per patient (0.53 vs. 0.31; $P < 0.001$) and overall ADR (29.1 vs. 20.3%; $P < 0.001$). It was also able to identify significantly more flat and sessile polyps, as well as diminutive polyps (Wang et al., 2020b). In a subsequent study by the same group, tandem colonoscopies were performed for each study participant, where the patients were randomly assigned to groups that received either routine colonoscopy or CADe assisted colonoscopy first, followed immediately by the other procedure. They found that AMR was significantly higher with routine colonoscopy (40%) than with CADe assisted colonoscopy (13.89%) (Wang et al., 2020a). Real-time CADe during screening colonoscopy, tested on several hours of colonoscopy videos, were also found to have a high accuracy of almost 97% (Urban et al., 2018). In an elegant study by Urban et al., detection of polyps was done using deep neural networks (DNN), on 8641 hand-labeled images from screening colonoscopies performed in 2,000 patients. The system was then tested on 20 random colonoscopy videos. Initially, benchmarks were developed with the help of experts who identified all polyps in the test videos. The CADe system had an accuracy of 96.5% and could detect polyps well with minimum latency (Urban et al., 2018). In a recent study by Repici et al., a novel CADe system was evaluated for real-time detection of colonic polyps. The CADe system was able to detect significantly more adenomas with an adenoma detection rate of 58% irrespective of withdrawal time. Adenomas detected per colonoscopy were also higher in the GI-Genius^{TM} group (mean 1.07 ± 1.54) than in the control group (mean 0.71 ± 1.20) (incidence rate ratio 1.46; 95% CI, 1.15–1.86). This improved ADR was mainly seen in polyps <5 mm and polyps with 5–9 mm diameter (Repici et al., 2020). These findings clearly show the utility of CADe systems in increasing the ADR and thereby reducing the rate of interval CRC.

Impact of CADe systems on healthcare costs in screening colonoscopy

The integration of CADe systems in colonoscopic screening for polyps can have significant implications on healthcare costs associated with these programs. The additional costs of integration of AI systems with endoscopy (Table 2) needs to be off-set by the reduction of CRC related treatment costs due to reduced incidence of both CRC as well as interval cancers, detection of tumors in early stages (Carcinoma *in situ*/Stage 1) owing to higher adenoma detection rates with AI based systems. In countries like India, where out-of-pocket expenses

TABLE 2 Approximate costs of integrating AI based tools into the colonoscopy screening programs.

Detailed cost analysis for AI based tools integration with CRC screening	Approximate cost per procedure (USD)
Cost of the software*	
A	30
B	16
Additional cost of upgraded endoscopy processors and scopes	
A	16
B	20
Approximate training cost	Negligible with current products on the market**
Total additional cost per procedure	41

*The cost of two available products in India (A & B) were obtained from manufacturers. Assuming the performance of 1,000 colonoscopies with each product, the approximate cost of AI per procedure was calculated. **Cost of training is minimal in India since all colonoscopies are being performed by trained Gastroenterologists.

are significant and account for a major proportion of the overall cost of treatment, measures that can address the financial aspects of a procedure that is almost universally indicated could have profound downstream implications. Unfortunately, due to the current nascent role of AI-based systems in CRC screening, there is very little data as to the objective effect of these systems on cost-effectiveness. On the one hand, considering the major healthcare expenditure is contributed by cancer treatment in most developing countries as well as emerging economies, it would follow that effective screening tools that could diagnose the cancer in a pre-malignant state will reduce cancer incidence and result in significant cost-saving (Ouakrim et al., 2015; Senore et al., 2019). As discussed in the previous section, the integration of CADe systems have shown measurable increases in ADR which would translate to significant reduction in the incidence of CRC at the population level. But from a point of view of cost-benefit analysis, however, this must off-set the increasing costs of polypectomy, histopathology evaluation of the increased number of samples that are being generated as a direct result of the CADe system.

In a study published recently by Areia et al., a Markov model microsimulation was performed using colonoscopy without and with AI for CRC screening. A hypothetical cohort of 100,000 individuals aged 50–100 years; and who were at average risk for CRC(no personal or family history of colorectal cancer, adenomas, inflammatory bowel disease, or hereditary colorectal cancer syndrome) were included. Assuming a screening uptake of 60%, the initial analysis compared the hypothetical costs of screening colonoscopy with and without AI, assuming a colonoscopy was performed every 10 years, starting at age 50, until age 80 years. Individuals were followed until age 100 years. The relative reduction of incidence of CRC was found to be higher in the group employing colonoscopy with AI (48.9%) as compared to the colonoscopy without AI group (44.2%) (4.8% incremental gain). A similar trend was observed in CRC mortality which showed a 3.6% incremental gain of AI integrated colonoscopy screening. Despite the increased cost of polypectomy and histopathology evaluation, AI detection tools decreased the costs per screened individual to $3,343, from $3,400 ($57 per individual screened). In a secondary analysis, they assessed the effect of a once-in-life screening colonoscopy at age 65 years among individuals with average risk aged between 65 and 79 years. Even with this model, there were significant cost reductions observed in the microsimulation with AI-based tools as compared to conventional colonoscopy (Areia et al., 2022). This was the first study to highlight the important implications of AI detection tools on financial aspects of CRC prevention programs. It is also important to note, that the primary analysis in the study assumed a 60% uptake of screening. Assuming a 100% uptake of screening, i.e., assuming higher levels of acceptance and better penetration and accessibility of preventive programs; they found a 29.1% reduction in colorectal cancer incidence and 31.6% reduction in colorectal cancer mortality in the colonoscopy with AI scenario compared with colonoscopy without AI, resulting in a saving of $94 per person. These findings were tailored to the healthcare system and insurance costs of a single country (USA). However, similar models should be explored for country specific healthcare systems in order to demonstrate the universal effect of AI detection tools on financial aspects of CRC screening. There are inherent limitations to the microsimulation model that was adopted to demonstrate the cost saving aspect of AI detection tools. These limitations include many assumptions on the patient behavior, acceptance, and implementation of screening programs. However, these limitations notwithstanding, it highlights a very intriguing area that can inform future efforts to integrate AI detection tools in our everyday practice.

The role of CADx system as an additional cost-saving strategy

As opposed to CADe systems, CADx systems can characterize the polyps as neoplastic or hyperplastic based on the AI diagnostic tool adopted (Rodriguez-Diaz et al., 2021). These systems are still under intense study and the routine implementation of which, could be a potentially disruptive technology that could usher in a new age in CRC screening programs. Essentially, the advanced diagnostic capabilities of CADx systems could open up the possibilities for two alternate strategies in CRC screening—"Resect and discard"

TABLE 3 Relevant classification of important references cited in the article.

Categories of references	References
CRC epidemiology, burden and prevalence	Khuhaprema and Srivatanakul, 2008; Corley et al., 2014; Dolatkhah et al., 2015; Aran et al., 2016; Kolligs, 2016; Marley and Nan, 2016; Arnold et al., 2017; Deng, 2017; Veettil et al., 2017; Mattiuzzi et al., 2019; Onyoh et al., 2019; Sung et al., 2021; Awedew et al., 2022; Shakuntala et al., 2022
Cost benefit analysis of CRC screening	Jansman et al., 2007; Tangka et al., 2008; Mahal et al., 2013; Rahman et al., 2013; Brenner et al., 2014; Färkkilä et al., 2015; Zorzi et al., 2015; Vahdatimanesh et al., 2017; de Moor et al., 2018; Jahn et al., 2019; Senore et al., 2019
AI based tools for detection of polyps during screening colonoscopy	Wang et al., 2015, 2020a,b; Bernal et al., 2017; Urban et al., 2018; Attardo et al., 2020; Repici et al., 2020; Sánchez-Peralta et al., 2020
AI based tools for Diagnosis of polyps during screening colonoscopy	Ignjatovic et al., 2009; Tischendorf et al., 2010; Gross et al., 2011; Ladabaum et al., 2013; Kominami et al., 2016; Misawa et al., 2016; National Institute for Health Clinical Excellence, 2017; Chen et al., 2018; Mori et al., 2018; Byrne et al., 2019; Yamada et al., 2019; Jin et al., 2020; Zachariah et al., 2020; Rodriguez-Diaz et al., 2021
Cost benefit analysis of AI based systems	Hassan et al., 2010; Kessler et al., 2011; Mori et al., 2020; Areia et al., 2022

and "Leave *in situ*" (Rex et al., 2011; Ladabaum et al., 2013). An adenomatous, diminutive polyp diagnosed by a CADx system which has a good accuracy, could just be resected and discarded, obviating the need for histopathology evaluation. In addition, a hyperplastic/mucosal polyp as diagnosed by CADx system in real time (i.e., during the colonoscopy) could potentially be left *in situ* as they have no malignant potential. This will drastically reduce the costs associated with polypectomy and histopathology evaluation of the biopsy samples that are otherwise the standard of care. Additionally, these measures could have far-reaching implications in logistical considerations of CRC screening programs, reduction of man-power and specialized equipment thereby increasing the operational efficiency, penetration, accessibility, and uptake of these programs. As demonstrated in the study by Areia et al. (2022), the uptake of screening could have profound effects on the ADR rate and subsequently on the cost-effectiveness of the CRC screening program.

The clinical application of optical diagnosis especially for diminutive polyps is increasingly being considered as the "next step" in colonoscopic screening of polyps (Ignjatovic et al., 2009; Hassan et al., 2010; Kessler et al., 2011). The National Institute for Clinical and Healthcare Excellence (NICE), which is responsible for setting the clinical standards in the United Kingdom (UK), approved the optical diagnosis of diminutive colorectal polyps using narrow-spectrum endoscopy in 2017. This was a significant step forward toward its implementation in clinical practice (National Institute for Health Clinical Excellence, 2017). However, this has not been widely used owing to its lack of specificity in non-expert hands. That is why, a reliable CADx system with good accuracy, fidelity and low latency could be the ideal alternative for optimal diagnosis of polyps.

Initially, CADx systems were able to differentiate between adenomatous from hyperplastic polyps while employing advanced image processing techniques like magnification chromoendoscopy or magnification NBI (Tischendorf et al., 2010; Gross et al., 2011; Kominami et al., 2016). However, these studies used AI techniques that were sub-optimal which limited its real-time application owing to the requirement complex post procedure image processing like manual segmentation of polyp margins and magnification techniques that are not widely available. The advent of DNN techniques changed the scenario and the newer CADx systems could diagnose polyps with minimal latency. In a prospective study of 41 patients, a CADx system was testes for diagnosing adenomatous polyps. The system showed a diagnostic accuracy of 93.2% for a real-time diagnosis on 118 colorectal lesions which was evaluated with NBI. Among the patients with small polyps, an impressive 92.7% showed concordance between the CADx diagnosis and the pathological findings (Zachariah et al., 2020). In another intriguing study, a novel CADx system was able to improve the overall accuracy of polyp diagnosis to 88.5% from 82.5% among controls ($P < 0.05$). This effect was especially pronounced among novices with limited training in using enhanced imaging techniques for polyp characterization, where the accuracy jumped from 73.8 to 85.6% (Jin et al., 2020). These findings indicate the feasibility of implementation of CADx systems in clinical practice.

A recent multicentric study, published by Mori and colleagues attempts to explore the financial implications of a novel CADx system (Mori et al., 2020). In this study, an add-on analysis was performed on a clinical trial that assessed the efficacy of a novel CADx system in differentiating neoplastic polyps from non-neoplastic polyps. The average cost was estimated for two situations, namely a Leave *in situ* strategy for supported by the AI prediction for diminutive rectosigmoid polyps, and a resect-all-polyps strategy. The gross annual costs for screening colonoscopies were considered based on data provided under public health insurances in 4 different countries. The novel CADx system could correctly differentiate neoplastic polyps with 93.3% sensitivity, 95.2% specificity, and 95.2% negative predictive value. This resulted in 105 polyps which were removed and 145 polyps which were left *in situ*. These strategies led to significant reductions of the average colonoscopy cost and the gross annual reimbursement for colonoscopies by 6.9% and 12.3 million dollars in England, 18.9% and 149.2 million dollars in Japan, 10.9% and 85.2 million dollars in the United States, and 7.6% and 1.1 million dollars in Norway compared to the resect-all-polyps strategy. This study clearly demonstrates the impact CADx systems could have on healthcare costs for CRC prevention programs and merits further studies to establish its role as an indispensable tool in CRC prevention programs worldwide.

Conclusions and future directions

AI-based detection tools and CADx systems are the way forward in CRC prevention. These tools can not only reduce the incidence of CRC through improved ADR, but it can have profound implications on cost reduction. This would result in better results in cost-effectiveness analysis and have far-reaching implications in mid-income and emerging economies like India. Apart from establishing the validity of optical diagnosis of polyps using CADx systems, future studies that utilize AI tools to predict the surveillance interval for colonoscopy for individual polyps based on morphological and clinical characteristics could represent a paradigm shift in our standard practices for CRC screening. This could help in re-allocation of resources in an efficient and streamlined manner so as to ensure the right patients get screened regularly, while patients at low risk of recurrence need not be subjected to repeated procedures (Mori et al., 2018, 2020). Cost reduction by using this strategy, if established could be an additional benefit while still maintaining efficacy and ADR at levels higher than what is currently been observed in most countries.

Additional studies that attempt to collate the total cost savings from implementation of CADx systems at the community level by obviating the need for histopathological correlation while adopting strategies like "Resect and discard" and "Leave *in situ*" needs to be performed either by simulation modeling or by longitudinal studies could highlight the true impact of AI based tools on CRC screening. In India, these tools could have incremental effects in addition to cost reduction by reducing the resources (human and equipment), infrastructure and logistical roadblocks that currently hamper the accessibility of CRC screening programs across demographics. Since CRC has shown a relentless upward trend in India, the time to consider organized screening programs aligning with the National Digital Health Mission is essential. The integration of AI tools for detection and characterization of colonic polyps with its significant cost reduction and additional benefits with regard to healthcare financial management, could be exactly what is needed to push for a national CRC prevention program (Table 3).

Author contributions

HR and PP performed the literature review and drafted the manuscript. NS reviewed the manuscript and provided important epidemiological insights. RV reviewed the final manuscript for critical insights. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A survey on detecting healthcare concept drift in AI/ML models from a finance perspective

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Data is incredibly significant in today's digital age because data represents facts and numbers from our regular life transactions. Data is no longer arriving in a static form; it is now arriving in a streaming fashion. Data streams are the arrival of limitless, continuous, and rapid data. The healthcare industry is a major generator of data streams. Processing data streams is extremely complex due to factors such as volume, pace, and variety. Data stream classification is difficult owing to idea drift. Concept drift occurs in supervised learning when the statistical properties of the target variable that the model predicts change unexpectedly. We focused on solving various forms of concept drift problems in healthcare data streams in this research, and we outlined the existing statistical and machine learning methodologies for dealing with concept drift. It also emphasizes the use of deep learning algorithms for concept drift detection and describes the various healthcare datasets utilized for concept drift detection in data stream categorization.

KEYWORDS

concept drift, data stream, drift detection methods, unsupervised learning, feature (interest) point selection

Introduction

Machine Learning (ML) is a set of methods, techniques, and tools for diagnosing and prognosing medical issues (Kralj and Kuka, 1998). ML is used to forecast illness progression, extract medical knowledge for outcome study, plan and support therapy, and manage patients. ML is also used for data analysis, such as recognizing regularities in data by successfully dealing with defective data, interpreting continuous data used in the Intensive Care Unit, and intelligent alerts, which improves monitoring (Strausberg and Person, 1999). Successful machine learning approaches can help integrate computer-based systems into healthcare, making medical specialists' work easier and better, and enhancing efficiency and quality.

Society pays for healthcare services through healthcare finance. Healthcare finance includes accounting and financial management. Accounting measures a business's activities and finances in financial terms, while financial management (corporate finance) applies theory and concepts to help managers make better decisions.[1] Depending on disease severity, many AI/ML models anticipate financial costs. Concept drift occurs as illness severity grows and treatment costs change. The model's alteration owing to data changes is called concept drift. In this study, we will discuss concept drift, its types, and strategies for handling concept drift in healthcare and financial data.

In our paper, we outline the following:

- ➢ Define concept drift in the healthcare domain and different drift types
- ➢ Review the work done for handling concept drift in the healthcare sector
- ➢ Classification techniques to handle concept drift

Concept drift and its types

Concept drift is most commonly associated with an online supervised learning scenario in which the relationship between the input data and the target variable changes over time (Gama et al., 2014). As a result of this, the error rate of the model increases which leads to the degradation of models' prediction results causing drift. Concept drift is also referred to as model drift or model decay in AI terminologies. Due to concept drift, the model misclassifies the data during the classification technique (Liu et al., 2017b) as shown in Figure 1.

Example: In the healthcare domain, the model created to predict the finance involved in treating a patient or insurance amount to be claimed from the company changes due to an increase in the complexity of the disease.

Types of concept drift

Figure 2 depicts different types of concept drift.

- **Sudden**—Sudden changes in health parameter values.
- **Gradual**—Concept is diminished slowly by another concept. For example, an increase in blood pressure leads to heart disease problems.
- **Recurring**—Changes reappear over the period. Example: Diabetic mellitus disease problems would reappear if there is a change in food habits.
- **Incremental**—Changes happen slowly over time.

Table 1 describes the different terminologies used to refer to different types of concept drift used in various works.

Figure 3 depicts the different ways of monitoring the occurrence of concept drift in data streams. The following are some of the ways:

- We can monitor the changes in data distribution
- We can monitor the feature changes in predicting the occurrence of concept drift.
- We can monitor the predictions of the classifier.
- We can monitor the labels of the data generated over time in finding the concept drift.

We picked potential papers based on the following inclusion criteria to determine applicable techniques.

- The method must be innovative for drift detection or integrate drift detectors into prediction systems.
- We listed all the papers related to different categories of drift detection from different authenticated journal databases.
- Papers related to concept drift in the healthcare sector are also listed.

In order to describe the review process involved in the manuscript to detect concept drift in healthcare application the following Figure 4 is used.

Background review

General framework to detect concept drift

There are four stages in a generic framework for drift detection as shown in Figure 5.

Stage 1 (Data Retrieval): Data retrieval extracts data chunks from data streams. Because a single data instance cannot infer the general distribution, data stream analysis jobs require knowledge of how to arrange data pieces into meaningful patterns (Lu et al., 2016; Ramirez-Gallego et al., 2017).

Stage 2 (Data Modeling): Data modeling abstracts the returned data and extracts the sensitive features that most affect a system if they drift. Sample size reduction, or

1 Available online at: https://account.ache.org/iweb/upload/ReiterSong_Ch1-4e0b591e.pdf.

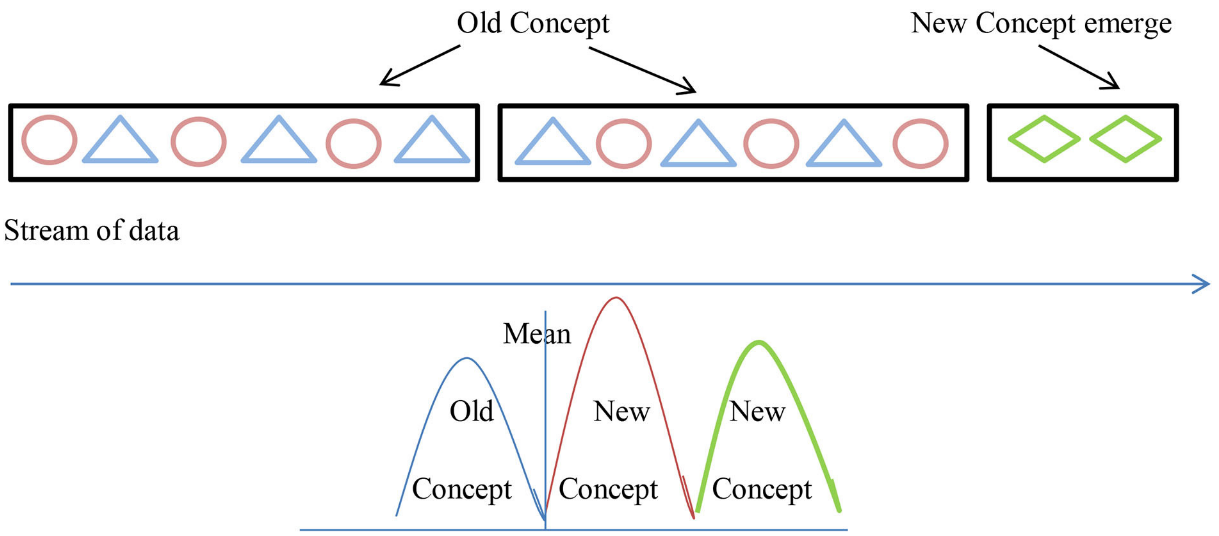

FIGURE 1
Concept drift.

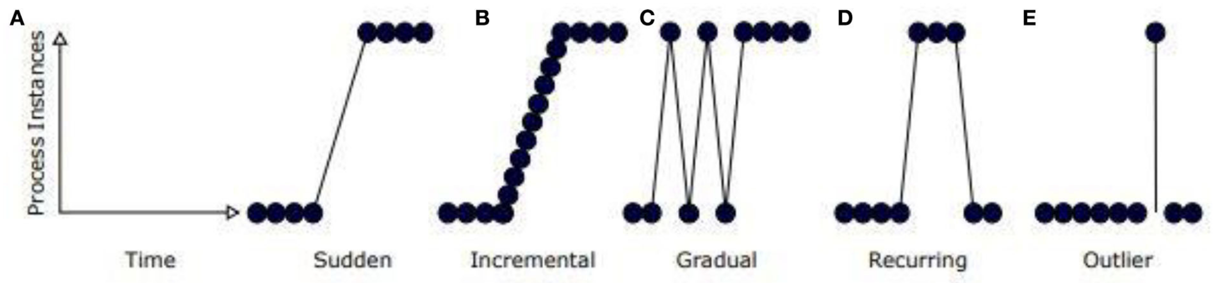

FIGURE 2
(A–E) Types of concept drift.

dimensionality reduction, to meet storage and online speed needs, is optional (Liu et al., 2017a).

Stage 3 (Test Statistics Calculation): In Stage 3, distance or dissimilarity is estimated (Test Statistics Calculation). The drift's severity is assessed, and hypothesis test statistics are prepared. This is the hardest aspect of concept drift detection. How to define an accurate dissimilarity assessment is unknown. Dissimilarity measurements can evaluate clustering (Silva et al., 2013) and compare sample sets (Dries and Ruckert, 2009).

Stage 4 (Hypothesis Test): Stage 4 (Hypothesis Test) uses the *p*-value to determine the statistical significance of Stage 3's change. Stage 3 test statistics are used to evaluate drift detection accuracy by showing their statistical bounds. Without Stage 4, Stage 3 test statistics cannot calculate the drift confidence interval, which reflects the likelihood that the change is due to concept drift rather than noise or random sample selection bias (Lu et al., 2014).

Concept drift in healthcare

On a multi-label hospital discharge dataset (Stiglic and Kokol, 2011) comprising diagnosis information, the suggested method employs relative risk and phi-correlation. The monthly discharge statistics and motion charts for visualization are used to detect concept drift. Static and dynamic ensemble classifiers are used to determine the accuracy and recommend the optimal classifier to use during concept drift.

TABLE 1 Concept drift by the probabilistic source of change (Bayram et al., 2022).

Primary term	Sudden drift	Gradual drift	Recurring drift	Incremental drift
Alternative terms	Abrupt drift	Evolutionary drift	Recurring contexts	Stepwise drift
	Concept shift			
	Revolutionary drift		Replacing drift	Development drift
	Immediate drift			

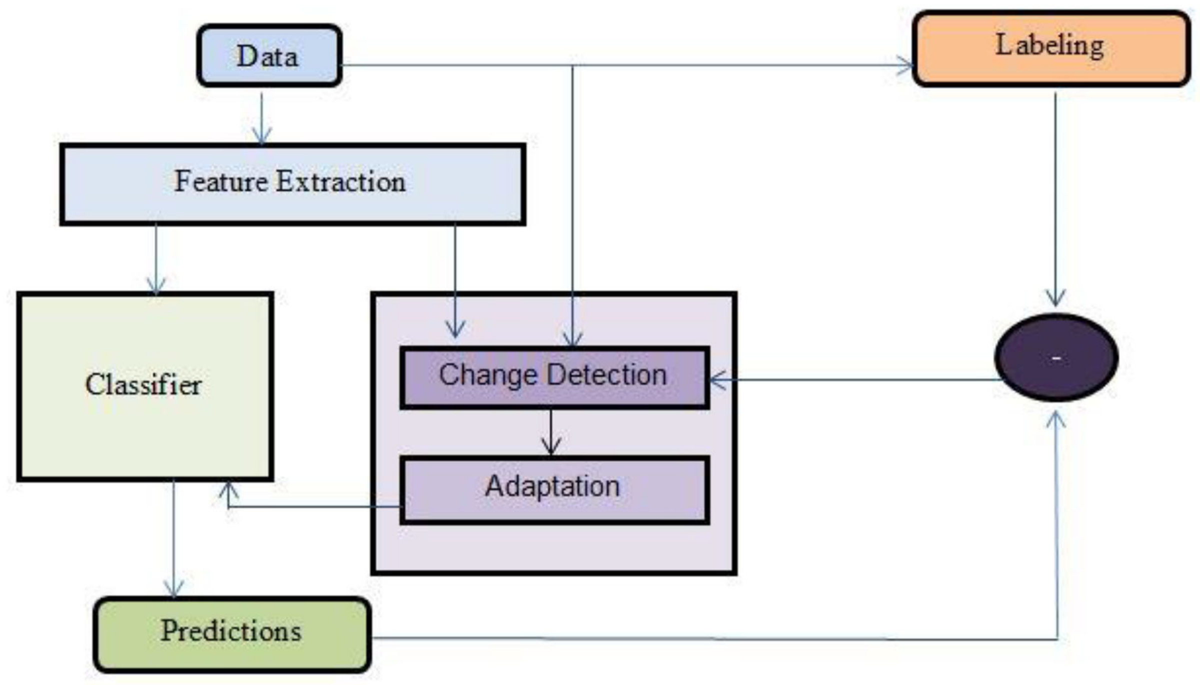

FIGURE 3
Different ways of occurrence of concept drift.

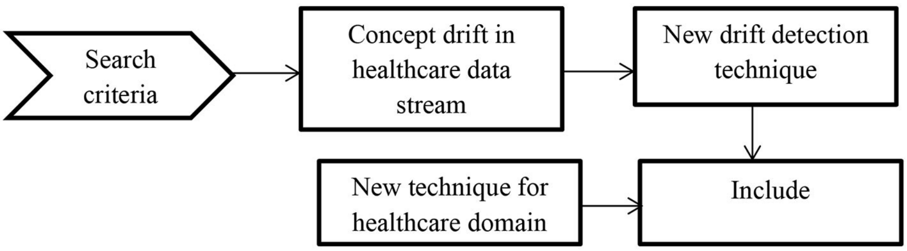

FIGURE 4
Systematic review process of concept drift.

Medical sensors that measure for general healthcare or rehabilitation (Toor et al., 2020) may be switched to ICU emergency procedures if necessary. When data have skewed class distributions, which is commonly the case with medical sensors' e-health data, detecting concept drifts becomes more difficult. The Reactive Drift Detection Method (RDDM) quickly finds long concepts. However, RDDM is error-prone and cannot handle class imbalance. The Enhanced Reactive Drift Detection Method (ERDDM) solves concept drift in class-imbalanced data streams.

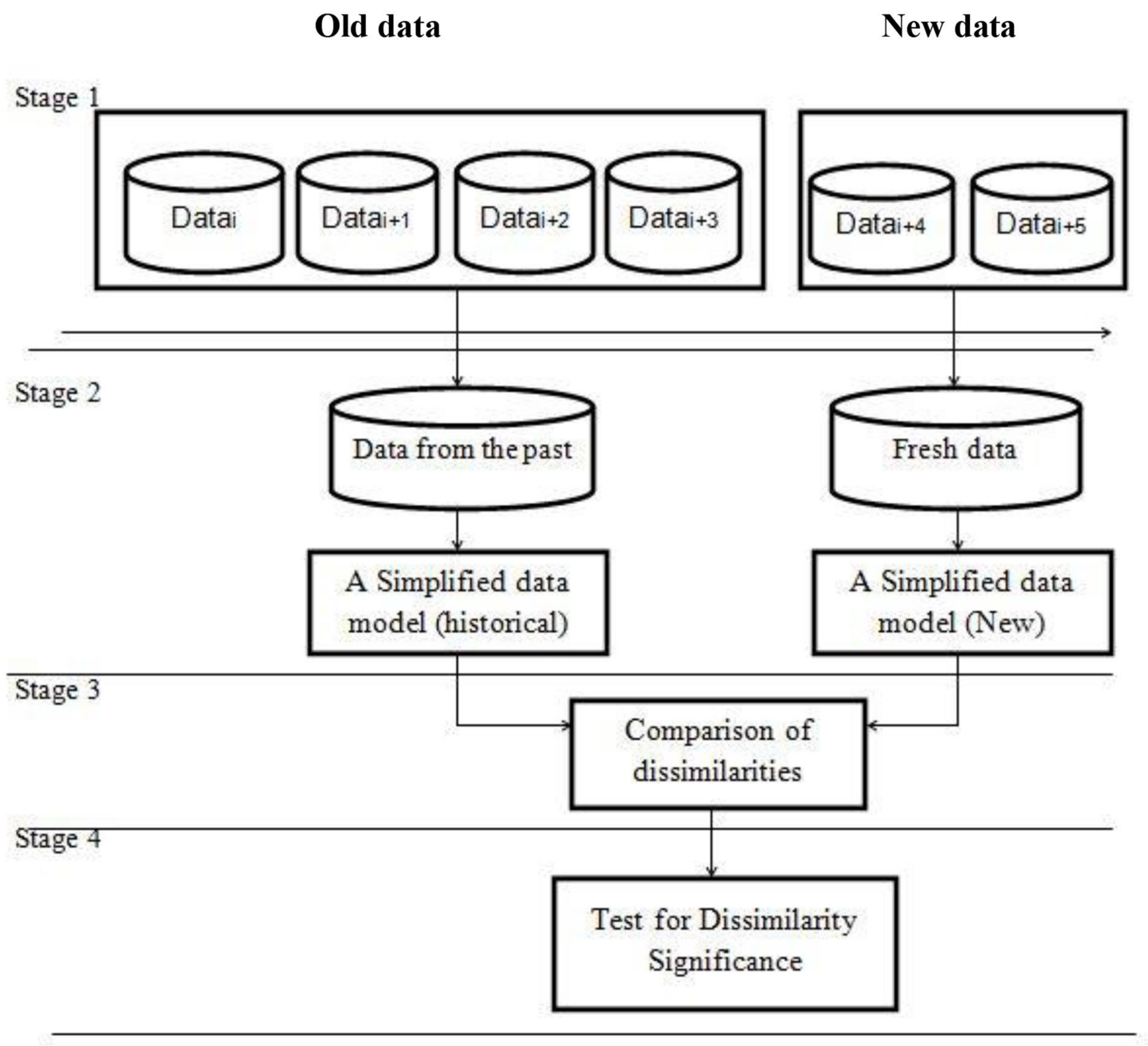

FIGURE 5
An overall framework for concept drift detection (Lu et al., 2019).

We compared ERDDM to three recent techniques for prediction error, drift detection delay, latency, and data imbalance.

Clinicians triage patients referred to a medical facility using referral documents (Huggard et al., 2020), which contain free text and structured data. By training a model to predict triage decisions from referral documents, we may partially automate triage and make more efficient and methodical decisions. This task requires robustness against triage priority changes due to policy, budget, staffing, or other considerations. Concept drift occurs when document features and triage labels change. The model must be retrained to reflect these changes. This domain uses the unique calibrated drift detection method (CDDM). CDDM outperformed state-of-the-art detectors on benchmark and simulated medical triage datasets and had fewer feature drift-induced false positives.

Calibration drift detection alerts users to model performance degradation (Davis et al., 2020). Our detector maintains a rigorous calibration measure using dynamic calibration curves, a new method for tracking model performance as it grows. An adaptive windowing (Adwin) strategy monitors this calibration parameter for drift as data accumulate (Wang and Abraham, 2015).

In this study, a hip replacement dataset surgical prediction model was created (Davis et al., 2020). Concept drift is indicated by data distribution changes that increase mistake rate and classifier performance. The trigger-based ensemble method handles concept drift in surgical prediction by processing each sample and adapts the model quickly to data distribution changes.

Deep learning can detect early infection in CT, MRI, and X-Ray images of sick individuals from medical institutions or public databases. Analyzing infection rates and predicting outbreaks uses the same methodology. Many open-source pre-trained classification or segmentation models are available for the intended study. For example, transfer learning improves COVID-19 identification and prediction in medical picture datasets (Prashanth et al., 2022).

Table 2 describes the summary of concept drift detection methods in healthcare datasets. It briefs the drift detection method, the healthcare datasets used, the hypothesis test, features, and the given method's drawbacks.

Categories of concept drift detection

There are two categories of detecting concept drift:

- Supervised
- Unsupervised

Supervised methods of concept drift detection categories

Performance-based Methods

This section examines performance-based concept drift detection techniques. Depending on the mechanism employed to identify performance dips, these techniques can be divided into one of several categories.

From the perspective of healthcare, performance-based techniques monitor the vital parameter values of patients' records. Any changes in the parameter values will alert the signal to take immediate actions. Following are some of the techniques used to monitor the performance of healthcare data:

- Statistical process control/Error rate-based methods
- Window based methods
- Sequential analysis
- Ensemble methods

Statistical process control/error rate based methods

Statistical process control checks our model's error. This is especially crucial while running production as the performance changes over time. Thus, we would like to have a system that will issue an alarm if the model passes the specified error rate.

Statistical process control methods are mentioned below:

- ***DDM—Drift detection method***: It models a number of errors as a binomial random variable. The key is to monitor the error rate. The parameters to monitor the error rate includes μ that is average error rate and σ, i.e., standard deviation (Gama et al., 2004).

p_t = error rate of algorithm/probability of misclassification

$$\mu = np_t \text{ and } \sigma = \sqrt{\frac{p_t(1-p_t)}{n}} \tag{1}$$

μ = mean, σ = Standarddeviation, n = numberof samples
To alert if drift occurs, it uses the following equation

$$p_t + \sigma_t \geq p_{\min} + 3\sigma_{\min} \tag{2}$$

$p_{\min}$ = minimum value of the error rate
$\sigma_{\min}$ = minimum value of standard deviation

- ***EDDM—Early drift detection method:*** It uses the distance between two consecutive errors rather than a number of errors. The distance should stay constant and any variations in the distance lead to drift. The method is good at detecting gradual concept drift (Baena-Garcia et al., 2006).

Warn and start caching:

$$\frac{p_t + 2\sigma_t}{p_{\max} + 2\sigma_{\max}} < 0.95 \tag{3}$$

Alert and reset max

$$\frac{p_t + 2\sigma_t}{p_{\max} + 2\sigma_{\max}} < 0.90 \tag{4}$$

- **CUSUM Test:**

The CUSUM test (Manly and Mackenzie, 2000) calculates the difference of observed values from the mean and warns of concept drift if it exceeds a user-defined threshold. The cumulative total indicates concept drift when the error mean is significantly different from zero. The test alerts the user if the log-likelihood ratio of two probabilities before and after change exceeds this threshold.

$$T_w^t = log\frac{P(x_w, \ldots, x_t|P2)}{P(x_{w,\ldots,x_t}|P1)} \tag{5}$$

The test declares a change when g_t is greater than the above equation threshold.

$$g_t = S_t - m_t \tag{6}$$

$S_t = \sum_{i=1}^{t} s_i$ = ratio of log-likelihood between the two probabilities
$m_t = \min_{1 \leq i \leq t} S_i$

TABLE 2 Drift detection methods in healthcare datasets.

References	Drift detection methods	Health care datasets	Hypothesis test	Pros	Cons
Stiglic and Kokol (2011)	Motion charts for drift detection in the detection of sudden concept drift	NHDS data	Relative risk and phi-correlation	Visualization helps select abnormally dynamic features	Detects only one type of drift. i.e., (sudden drift)
Toor et al. (2020)	Enhanced Reactive Drift Detection Method (ERDDM)	Medical Sensors measuring for general healthcare or rehabilitation.	–	To address the class imbalance, SMOTE was used.	Handles abrupt and gradual drifts.
Huggard et al. (2020)	calibrated drift detection method (CDDM)	benchmark and synthetic medical triage datasets	Nemenyi *post-hoc* test to compare the detection methods.	CDDM is h less prone to false positives.	A single system that can handle all changes in triage priorities.
Davis et al. (2020)	Adaptive windowing (Adwin)	Department of Veterans Affairs (VA)	–	Calibration curves show model performance over anticipated probability ranges. Loess smoothing or logistic regression is used to produce these curves. Addresses all types of drift	Accuracy in the detection of different types of drift can be improved.
Beyene et al. (2015)	Trigger-based Ensemble (TBE)	hip-replacement dataset	Nemenyi *post-hoc* test	Automate the prediction task of surgery.	The ensemble size does not become overly large

➢ **Page–Hinckley Test:**

The test detects an abrupt change of the average of a Gaussian signal and the detection process (Qahtan et al., 2015) consists of running two tests in parallel, testing between the no-change hypothesis H0: $r > n$ and the change hypothesis H1: $r > n$.

To detect an increase in average, we calculate:

$$U_n = \sum_{i=1}^{n} (x_i - m_0 - \frac{\delta m}{2})\ for\ n{\geq}1 \text{ and } U_0 = 0 \tag{7}$$

$m_n = \min_{0\leq k\leq n}(U_k)$ for $n \geq 1$

To detect a decrease in average, we calculate:

$$U_n = \sum_{i=1}^{n} (x_i - m_0 - \frac{\delta m}{2})\ for\ n{\geq}1 \text{ and } U_0 = 0 \tag{8}$$

$M_n = \max_{0\leq k\leq n}(T_k)$ for $n \geq 1$

To alarm, we use $M_n - T_n \geq \tau$

➢ **Hoeffding Drift Detection Method (HDDM):**

The Hoeffding Drift Detection Method (HDDM) (Frías-Blanco et al., 2015) enhances DDM by utilizing Hoeffding inequality to identify significant alterations in the performance estimate's moving average.

The Hoeffding bound is defined as:

$$\epsilon = \frac{R^2 \ln(\frac{1}{\delta})}{2n} \tag{9}$$

ϵ = Hoeffding bound

R: Probability range. For probability, the range is 1, and for information gain, log c, where c is the number of classes.

δ: Confidence. 1 minus the required chance of choosing the right attribute at every given node.

n: Count of samples.

The variants in the HDDM family include:

✓ **Hoeffding drift detection with an A_test (HDDM$_A$):** Methods for learning in data stream situations exist that compute confidence intervals for various parameters (such as error rate) while taking into account well-known distributions. The Hoeffding drift detection method with an A_test (Frías-Blanco et al., 2015) considers the difference between moving averages. It estimates the error ϵ_α given a significant level of at most α.

✓ **Hoeffding drift detection with weighted moving averages (HDDM$_W$):** For weighted moving averages (Frías-Blanco et al., 2015), there is a broader statistical test that is quick and easy. Given that they are more likely to occur, the current real values are given greater weight than older ones in this situation.

✓ **Fast Hoeffding Drift Detection Method (FHDDM):** The FHDDM algorithm (Pesaranghader and Viktor, 2016) uses a sliding window and Hoeffding's inequality to compute and compare the highest probability of correct predictions with the most recent probability to detect drift.

✓ **Stacking fast Hoeffding drift detection method (FHDDMS):** The Stacking Hoeffding Drift Detection Approach (FHDDMS) (Pesaranghader et al., 2018), which maintains windows of various sizes, expands the FHDDM method. In other words, a short and a long sliding window are combined. This strategy's justification is to cut down on false negatives and detection delays. According to logic, a short window should be able to identify abrupt drifts more quickly than a lengthy window, which should do so with a lower rate of false negatives.

✓ **Additive FHDDMS (FHDDMS$_{\text{add}}$):** FHDDMS$_{\text{add}}$ detects abrupt concept drifts with shorter delays and reduces false negatives for gradual drifts.

✓ **Exponentially Weighted Moving Average (EWMA):** EWMA for Concept Drift Detection adapts EWMA charts to detect classifier error rate changes (Ross et al., 2012). Time t computes the EWMA estimator's dynamic standard deviation Z_t and error rate $\hat{p}_{0,t}$. Concept drift is indicated if

$$Z_t > \hat{p}_{0,t} + L\sigma_{Zt} \tag{10}$$

The control limit, or parameter L, specifies how much Z_t must deviate from $\mu 0$ before a change is noted.

➢ **Extreme Learning Machine (ELM):** Extreme Learning Machine (ELM) (Huang et al., 2006) builds single-hidden layer feed-forward neural networks (SLFNs) by randomly selecting hidden nodes and calculating output weights. This technique provides good generalization performance at very fast learning speeds compared to gradient-based learning algorithms for feed-forward neural networks.

➢ **Dynamic Extreme Machine Learning (DELM):** DELM (Xu and Wang, 2017) online learns a double hidden layer structure to improve ELM performance. ELM's notion drift alarm increases the classifier's generalization power by adding hidden layer nodes. If concept drift surpasses a threshold or ELM accuracy, the classifier will be withdrawn and retrained with new data to learn new concepts.

➢ **Online sequential learning algorithm for feed-forward networks (OS-ELM):** Single-layer concealed a fast and accurate online sequential learning approach (OS-ELM) has built feed-forward neural networks with additive and radial basis functions (RBF) hidden nodes (Liang et al., 2006). Any limited non-constant piecewise continuous function can activate an additive node, and any integral piecewise continuous function can activate an RBF node. The algorithm can also process chunked data. Only the number of concealed nodes must be selected.

TABLE 3 Contingency table (Agrahari and Singh, 2021).

		Actual→	
		0	1
Predicted ↓	0	TN	FN
	1	FP	TP

Sequential analysis-based methods

To determine how the context of the data stream has changed, the data instances are inspected one after the other. When the change in data distribution surpasses the predetermined threshold, it signals drift. The accuracy of the classifier is lowered as a result of concept drift. It can therefore be one of the methods used to identify concept drift in a particular data stream. Among the accuracy metrics of a classification model are recall, precision, F-measure, ROC, and AUC.

In Sequential analysis we monitor the contingency table. If the data are not stationary, we have different values in the table. If the data are not stationary, we have different values in the table. Rather than monitoring the contingency table values every time, we will monitor the four rates of the contingency table, i.e., precision, recall, sensitivity, and specificity to signal concept drift (Liu et al., 2016).

Liu et al. (2016) presented FP-ELM, which, like OS-ELM, can achieve incremental and on-line learning. Additionally, FP-ELM will apply a forgetting parameter to past training data based on current performance in order to adjust to possible changes after a new chunk is introduced.

Table 3 shows a categorical contingency table. A contingency table illustrates frequencies for specific combinations of two discrete random variables X and Y. The table cells contain mutually exclusive X–Y values.

TP = True Positive FP = False Positive TN = True Negative FN = False Negative

Precision $= \frac{TP}{TP+FP}$, Recall $= \frac{TP}{TP+FN}$, sensitivity $= \frac{TN}{TN+FN}$, specificity $= \frac{TN}{TN+FP}$

This method sequentially evaluates prediction results as they become available and concept drift is flagged when a pre-defined threshold is met.

Window-based methods

This method groups incoming data into a batch (or a window). Window-based methods have two windows. Figure 6 shows old data stream instances in the first window and new ones added afterward. These two window cases showed the drift and explained the data distribution change. This method can use either fixed or adjustable window sizes. A fixed window stays the same size during analysis. However, drift conditions change the adaptive window size. Drift shrinks the data window; no drift widens it (Agrahari and Singh, 2021).

From a healthcare perspective, the window can be considered as recording the patient's details every day or every hour and monitoring the changes over that period of time. Any

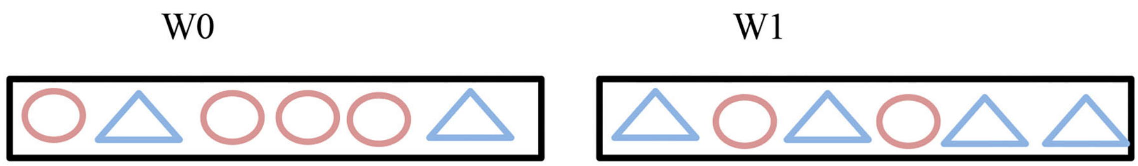

FIGURE 6
Window-based concept drift detection.

improvements or fluctuations in that period will be carefully noticed and actions will be further taken.

The different window-based methods are as follows:

- **Adaptive windowing (ADWIN and ADWIN2):** Adaptive windowing (Bifet and Gavalda, 2007) considers all partitions of the window and compares the distribution between two windows. Any changes in distribution between two windows signals concept drift. For each partition, the method calculates the mean error rate and compares its absolute difference to a threshold based on the Hoeffding bound and if the subpartition is violated then it drops the last element in the window.

$$\text{Drop the last element} \textit{if } |\mu_0 - \mu_1| > \theta_{Hoeffding} \tag{11}$$

Due to its low false positive and false negative rate, ADWIN performs effectively. The one-dimensional data that ADWIN can handle is its only drawback. It keeps different windows open. ADWIN2 is a modified version that uses less time and memory than ADWIN. The average distribution difference between two successive windows must be greater than a predefined threshold in order for drift to be detected. By identifying the slow, gradual drift, ADWIN2 gets around ADWIN's drawback. It requires O(log WS) memory and time if the window size is WS (Agrahari and Singh, 2021).

μ_0 – Error rate of W0
μ_1 – Error rate of W1

- **Detection Method Using Statistical Testing (STEPD):** Current and general accuracy is the rule. Two assumptions are made for this method: first, if the target concept is stationary, a classifier's accuracy for the most recent W examples will be equal to the overall accuracy from the start of learning; and second, a significantly lower recent accuracy signals that the concept is changing. Methods with an online classifier and monitoring its prediction errors during learning have been developed to detect concept drift in a limited number of samples. Nishida and Yamauchi (2007) created a detection approach that employs a statistical test of equal proportions.

The equation below calculates the statistic:

$$T(r_0, r_r, n_0, n_r) = \frac{\left|\frac{r_0}{n_0} - \frac{r_r}{n_r}\right| - 0.5\left(\frac{1}{n_0} + \frac{1}{n_r}\right)}{\sqrt{\hat{p}(1-\hat{p})}\sqrt{(1/n_0 + 1/n_r)}} \tag{12}$$

- **Wilcoxon Rank Sum Test Drift Detector (WSTD):** A novel two-window approach to STEPD-like concept drift detection in data streams. WSTD (de Barros et al., 2018) limits the older window size and employs the Wilcoxon rank sum statistical test instead of STEPD's test of equal proportions. The WSTD test equation is as follows:

$$z = \frac{(R - \mu_R)}{\sigma_R} \tag{13}$$

$\mu_R = population\ mean = n1\ \times\ (n1 + n2 + 1)$
$\sigma_R\ = standar\ deiation = \sqrt{\frac{n1*n2*(n1+n2+1)}{12}}$
n1 = n2 = Size of the smallest and largest samples.

- **Fishers Exact Test:** The test proposed three approaches: Fisher Test Drift Detector (FTDD), Fisher Square Drift Detector (FSDD), and Fisher Proportions Drift Detector (FPDD) (de Lima Cabral and de Barros, 2018). Fisher's exact test was employed to get the *p*-value, which is the only distinction between these approaches and STEPD.
- **Cosine Similarity Drift Detection (CSDD): The** Cosine Similarity Drift Detector (CSDD) produces the confusion matrix using a Positive Predictive Value (PPV) and the False Discovery (FDR) rates instead of TP and FP for each window. The Cosine Similarity (Hidalgo et al., 2019) between the vectors produced from the confusion matrices of the two windows indicates drift or warning.
- **McDiarmid Drift Detection Method (MDDM):** MDDM identifies concept drift using McDiarmid's inequality (Pesaranghader et al., 2017). MDDM works by sliding a window over the predictions and weighting the window entries. Recent entries are weighted more to highlight their importance. As examples are processed, the detection method compares the maximum weighted mean to the sliding window's weighted mean. When the weighted

means diverge beyond the McDiarmid inequality, concept drift is inferred.

- **Margin Density Drift Detection (MD3):** To signal drift, MD3 uses the number of samples mapped to a classifier's uncertainty zone (Sethi and Kantardzic, 2015).
- **Kolmogorov–Smirnov test (KS test):** A concept change detection technique called KSWIN (Kolmogorov–Smirnov Windowing) is based on the Kolmogorov–Smirnov (KS) statistical test. The KS test is a statistical test that makes no assumptions about the distribution of the underlying data. Data or performance distributions can be watched by KSWIN. The detector will accept an array of one-dimensional input. The KS test is run on identically sized windows, R and W. The distance of the empirical cumulative data distribution is compared using the KS test. KSWIN can identify concept drift if:

$$dist\ (R, W) > \sqrt{-\ ln\frac{\alpha}{r}} \tag{14}$$

Because R and W are derived from the same distribution, if the difference in empirical data distributions between them is too great, concept drift can be identified

Raza et al. (2015) provide unique covariate shift-detection techniques based on a two-stage structure for both univariate and multivariate time-series. The first stage detects the covariate shift-point in non-stationary time-series using an exponentially weighted moving average (EWMA) model-based control chart in online mode. The second step confirms the first stage's shift detection using the Kolmogorov-Smirnov statistical hypothesis test (K-S test) for univariate time-series and the Hotelling T-Squared multivariate statistical hypothesis test for multivariate time-series.

- **CIDD-ADODNN Deep learning framework:** The CIDD-ADODNN (Priya and Uthra, 2021) model classifies extremely imbalanced streaming data efficiently. The recommended adaptive synthetic (ADASYN) methodology weighs minority class examples based on learning difficulties to handle class imbalance data. Concept drift is detected using an adaptive sliding window (ADWIN).
- **Concept drift adaptation using Recurrent Neural Networks:** Recurrent neural networks (RNNs) are utilized to detect time series anomalies (Saurav et al., 2018). Since new data are added gradually, the model can adapt to data distribution changes. RNN predictions of the time series are used to discover anomalies and change points. A significant prediction error indicates deviant behavior.

Ensemble methods

Figure 7 depicts the ensemble method architecture. The above architecture has n models and combines the predictions of all models to predict the output. From a healthcare perspective, the ensemble method resembles the consulting decisions of multiple doctors to ensure the disease type and level before diagnosing.

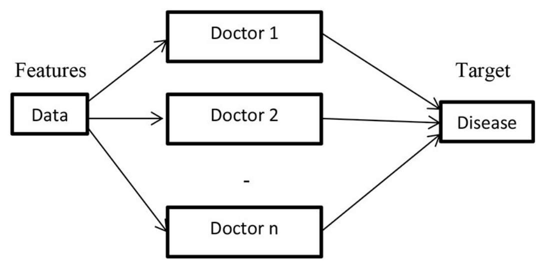

FIGURE 7
Ensemble methods.

The ensemble methods used for concept drift detection are as follows:

- **Streaming Ensemble Algorithm (SEA):** By adding a new learner for each new chunk of data until the maximum number of learners is reached, SEA (Street and Kim, 2001) automatically manages drift. Based on their performance with predictions, the learners are improved.
- **Accuracy-Weighted Ensemble (AWE):** An Accuracy-Weighted Ensemble (Wang et al., 2003) is a group of classification models where each model is carefully weighted according to how accurately they are projected to classify the test data in a time-evolving environment. The ensemble ensures that it is effective and resilient to concept-drifting streams.
- **Accuracy Updated Ensemble (AUE):** By utilizing online component classifiers and updating them in accordance with the current distribution, Accuracy Updated Ensemble (AUE) (Brzeziński and Stefanowski, 2011), a development of AWE, increases accuracy. Additional weighting function adjustments address issues with unintended classifier discarding seen in AWE.
- **Dynamic Weighted Majority (DWM):** Four strategies are employed by the dynamic weighted majority (DWM) (Kolter and Maloof, 2007) to counteract concept drift. It develops the ensemble's online learners, weights them depending on their performance, deposes them based on their performance, and adds fresh experts based on the ensemble's overall performance.
- **Learn++.NSE**: A group of learners is trained in Learn++.NSE (Polikar et al., 2001) using examples of data chunks. The weighting of the training instances is based on the ensemble error for this particular case. Learn++.NSE increases the example's weight to 1 if the ensemble properly classifies it, otherwise, it is penalized to $w_i = 1/e$. Based on their mistakes in the previous and

current chunks, the ensemble of learners is weighted using the sigmoid function.

- **Adaptive Random Forest (ARF):** ARF (Gomes et al., 2017) uses efficient resampling and adaptive operators to tackle concept drifts without data set optimization.
- **DDD:** DDD regulates learner diversity by including low and high-diversity ensembles. The low diversity ensemble and high diversity ensemble are used after drift detection.
- **DDE:** Bruno Maciel et al., 2015 made a small ensemble to control how three drift detectors work and block their signals at both the warning level and the drift level. Depending on how sensitive the DDE is, it needs a certain number of detectors to confirm an alarm or drift level. Another parameter is the type of drift mechanism that is used. But each sensitivity setting has a default detector setup that goes with it.

Data distribution methods

To determine the contextual shift, this kind of drift detection approach compares examples of recent and previous data. These techniques often examine the statistical significance and are used in conjunction with the window-based approach. The location of the drift can be determined by computing the change in data distribution. As a result, computational costs might result and it depicted in Figure 8.

From a healthcare perspective, the distribution of current vital health parameters are studied with the previous day/week or previous hour, and even before diagnosis and after diagnosis. The patient's health parameters are carefully observed and studied and, depending on the health parameter value distributions, the doctor can further extend the medications to the patient or discharge the patient from the hospital.

- SyncStream (Shao et al., 2014) is a prototype-based categorization model for evolving data streams that dynamically models time-changing ideas and offers local predictions. By constantly keeping a collection of prototypes in a new data structure known as the P-tree, SyncStream captures developing notions instead of learning a single model on a sliding window or ensemble learning. The prototypes are created using limited clustering and error-driven representativeness learning. Heuristics based on PCA and statistics are used to detect abrupt idea drift in data streams.
- PCA-Based Change Detection Framework (Qahtan et al., 2015) methodology is built on estimating data for a subset of key constituents. Densities in reference and test windows are estimated and compared for each projection. Then, one of the divergence measures determines the change-score value. The largest change score among the several principal components is taken into account as the final change score by giving equal weight to all of the selected principal components.
- A technique by Ditzler and Polikar (2011) uses an adjustable threshold to calculate the Hellinger distance as a measure to determine whether drift exists between two batches of training data.
- A brand-new test, outlined in Bu et al. (2018), for detecting changes without using the probability density function that works online with multidimensional inputs has been created and is based on the least squares density-difference estimation method. By using a reservoir sampling mechanism, the test can start running right away after configuration and does not require any assumptions about the distribution of the underlying data. Once the application designer has established a false positive rate, the requested thresholds to detect a change are automatically derived.
- A local drift degree (LDD) (Liu et al., 2017a) measurement can track alterations in local density over time. After a drift, we synchronize the regional density disparities in accordance with LDD rather than suspending all historical data.
- Reactive Robust Soft Learning Vector Quantization (RRSLVQ) (Raab et al., 2020) is a method for detecting concept drift that combines the Kolmogorov–Smirnov (KS) test with the Robust Soft Learning Vector Quantization (RSLVQ).

Multiple hypothesis based methods

These algorithms are unusual in that they employ several hypothesis tests to track concept drift in various ways. The two types of multiple-hypothesis tests are parallel and hierarchical (Lu et al., 2019).

From a healthcare perspective, before diagnosing any disease, multiple tests should be done mandatorily. For a pandemic disease like SARS-CoV-2, the virus that causes COVID-19, testing specimens from your nose or mouth, NAATs, such as PCR-based tests, are most often performed in a laboratory. Furthermore, antigen tests and MRI scans of the chest have to be done to know the severity of the disease.

Two-stage covariate shift identification tests are available for both univariate and multivariate time series. The first stage uses an exponentially weighted moving average (EWMA) control chart to locate the covariate shift point in a non-stationary time series online. The second stage validates the shift found in the previous stage with the Kolmogorov–Smirnov statistical hypothesis test (K–S test) for univariate time series and Hotelling's T-squared multivariate test.

- The study by Yu et al. (2019) proposes a concept drift detection framework (LFR) for detecting concept drift and finding data points linked with the new concept. LFR can handle batch, stream, unbalanced, and user-specified parameters.

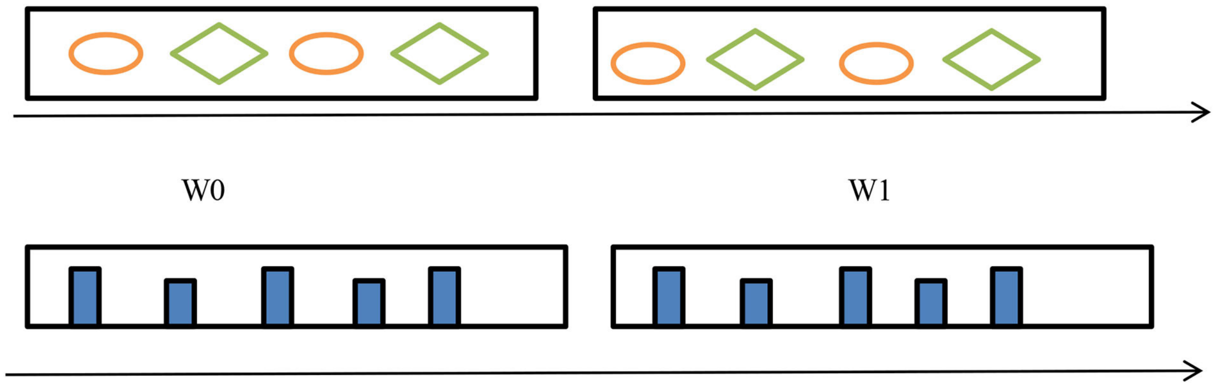

FIGURE 8
Feature distribution monitoring.

- As proposed by Yu et al. (2018), a rapid concept drift detection ensemble (DDE) that integrates three concept drift detection algorithms to improve drift detections. Accuracy improves without affecting execution time.
- This article (Alippi and Roveri, 2008) proposes a pdf-free extension of the standard CUSUM using the CI-CUSUM test, which somehow inherits the extended CUSUM's detection skills and computational intelligence philosophy. Non-stationary data can be detected via the CI-CUSUM test.
- A novel hierarchical hypothesis testing framework with a Request-and-Reverify technique detects idea drifts by asking for labels only when needed. The unique paradigm offers hierarchical hypothesis testing with classification uncertainty (HHT-CU) and attribute-wise "goodness-of-fit" (HHT-AG).
- A hierarchical hypothesis testing (HHT) system that can detect and adjust to concept drift in unbalanced data labels (such as recurrent or irregular, gradual, or abrupt). HLFR, a new drift detector, is implemented using the HHT framework by switching to adaptive training.

Unsupervised methods of concept drift detection categories are as follows

Clustering/novelty detection

In clustering, each batch of data is assigned to a particular group and if it is not assigned to any particular group, concept drift is declared, as shown in Figure 9.

From a healthcare perspective, we monitor all the health parameter values. After studying all health parameter values and reports the disease label is named.

The different clustering methods for stream data are as follows:

- **OLINDDA**—This method uses *k* means clustering and periodically merges known and unknown batches of data. If the latter, concept drift is flagged (Spinosa et al., 2007).
- **MINAS**—This method uses micro clustering and to gain efficiency it uses incremental clustering (Faria et al., 2013).
- **DETECTNOD**—This method uses discrete cosine transform to estimate the distances efficiently (Hayat and Hashemi, 2010).
- **Woo-Ensemble**—This method treats outliers as potential emerging class centroids (Ryu et al., 2012).
- **ECSMiner**—Stores and uses cluster summary efficiently (Masud et al., 2011).
- **GC3**—This method uses grid-based clustering (Sethi et al., 2016).

Feature distribution monitoring

The idea is to monitor each feature individually. We monitor two sub-windows, W0 and W1, and compare their feature distribution either through Pearson correlation (Change of concept) or through Hellinger distance (HDDDM) (Lee and Magoules, 2012) as shown in Figure 9. If we have many features then the monitoring of features will be very difficult, so we can use principal component analysis (PCA) (Qahtan et al., 2015) to reduce features so that the monitoring of features will be easier.

Model-dependent monitoring

Unsupervised methods suffer from a high rate of false alarms because they constitute that any changes in observations are a reason for performance degradation. It is known that not all changes in observations lead to performance degradation. To reduce false alarm rates, we estimate the posterior probability (Dries and Ruckert, 2009).

The unsupervised methods under model-dependent monitoring are as follows:

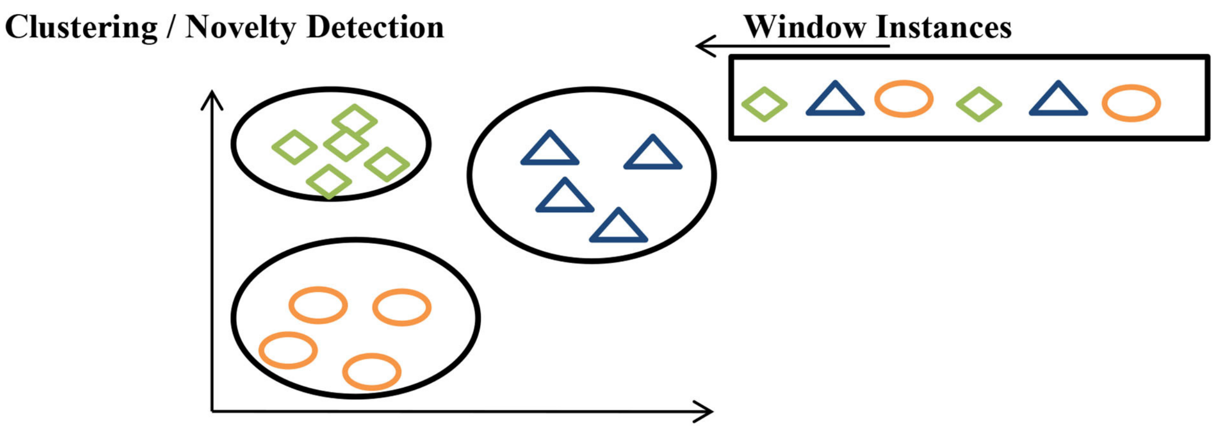

FIGURE 9
Clustering data streams.

- **A—Distance method:** This method uses a generalized Kolmogorov–Smirnov distance to estimate the posterior probability.

Healthcare datasets

Some of the various healthcare datasets used in concept drift detection include:

- **National Hospital Discharge Survey (NHDS) data**[2] The dataset contains hospital discharge records for approximately 1% of US hospitals.
- **MIMIC-III** (Johnson et al., 2016)—a freely accessible critical care database: MIMIC-III ("Medical Information Mart for Intensive Care") is a large, single-center database comprising information relating to patients admitted to critical care units at a large tertiary care hospital. Data include vital signs, medications, laboratory measurements, observations and notes charted by care providers, fluid balance, procedure codes, diagnostic codes, imaging reports, hospital length of stay, survival data, and more.
- **The Veterans Health Administration (VHA)** (Davis et al., 2020): It is one of three administrations within the Department of Veterans Affairs (VA), and is the largest integrated health system in the United States.
- **Hip-replacement dataset** (Clarke et al., 2015) from the orthopedics department of Blekinge hospital.
- **Il Paese Ritrovato Dataset**[3] a healthcare facility located in Monza that was created for the residential care of people affected by Alzheimer's disease.

2 Available online at: https://www.cdc.gov/nchs/nhds/nhds_questionnaires.htm.

3 Available online at: https://www.cfsitalia.com/en/projects/il-paese-ritrovato/.

Future research prospects

The following are some directions we can explore in the future:

- **Drug Manufacturing Process:** Changes in drugs can impact the economy of the company. Early information about the drugs could stop or increase further production.
- **Monitoring Health parameters during surgery:** Early information about the health parameters during surgery could help during diagnosis.
- **Pandemic disease information:** COVID-19 has disturbed regular processes in the health sector. Prior information could help to avoid further problems.
- **Deep Learning Techniques to address concept drift problems.** New techniques to handle concept drift problems in the health industry could resolve many problems.

Conclusion

This article investigated the concept of drift-handling algorithms designed for healthcare applications. It addresses supervised learning tasks where the aim is to generate a map of the feature instances, the target variables, and unsupervised learning tasks where there is an absence of class labels in the given instances. This article addresses the machine learning algorithms used to handle concept drift for medical domain problems. It also addresses different types of concept drift and how to handle them using implicit and explicit approaches. Different techniques for handling concept drift in the medical sector can be incorporated as future scope.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

Conceptualization: AM, SB, and HL. Data curation, methodology, writing—original draft, and formal analysis: AM and NC. Funding acquisition: HL. Investigation: AM and SB. Supervision: NC and SB. Validation: HML, SB, and AM. Writing—review and editing: SB, HML, HL, and AM.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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