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Prediction Models for Public Health Containment Measures on COVID-19 Using Artificial Intelligence and Machine Learning: A Systematic Review

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ABSTRACT

Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have expanded their utilization in different fields of medicine. During the SARS-CoV-2 outbreak, AI and ML were also applied for the evaluation and/or implementation of public health interventions aimed to flatten the epidemiological curve.

Methodology

We searched for the studies that are published between 2019 to 2023, later we performed the systematic review and extracted the conclusions related to COVID-19, Artificial Intelligence and Machine Learning.

Results

Our findings showed that quarantine should be the best strategy for containing COVID-19. Nationwide lockdown also showed positive impact, whereas social distancing should be considered to be effective only in combination with other interventions including the closure of schools and commercial activities and the limitation of public transportation. Our findings also showed that all the interventions should be initiated early in the pandemic and continued for a sustained period. Our systematic review evaluated the effectiveness of AI and ML to guide implementation of public health interventions aimed to contain SARS-CoV-2 pandemic.

Conclusions

Despite the study limitation, we concluded that AI and ML could be of help for policy makers to define the strategies for containing the COVID-19 pandemic.

Keywords: artificial intelligence; machine learning; COVID-19; public health interventions; prediction models; epidemic; pandemic; severe acute respiratory syndrome coronavirus-2.

Introduction

The COVID-19 pandemic which is caused by the SARS-CoV-2, as imposed the unpredictable challenges around the globe, which necessitates the innovative and adaptive strategies for public health containment measures. The spread of corona virus rapidly and its dynamic and complex nature has limited the ongoing public health approaches which we were using from decades, this also underscored the need for cutting-edge technologies. In this scenario, the integration of machine learning (ML) and artificial intelligence (AI) emerged as to transform the healthcare by offering the ways to revolutionize the development and implementation of predicted models which aimed to enhance public health containment measures for COVID-19. [1]

1.1 The Global Impact of COVID-19

By looking at the global perspective of COVID-19, it emerged in late 2019 and was marked as a life-threatening moment of the globe affecting humans. The virus rapidly speeded across borders, which caused widespread illness as it was contagious, the healthcare system got overwhelmed which caused significant social and economic disruptions. This overall situation demanded a swift and dynamic response from the global community irrespective of their relation to healthcare force or not. The traditional public health measures were somehow effective but faced many challenges in coping the health concerns related to COVID-19 and the evolving patterns of the pandemic, that was really a paradigm shift in approach related to COVID-19 pandemic. [2]

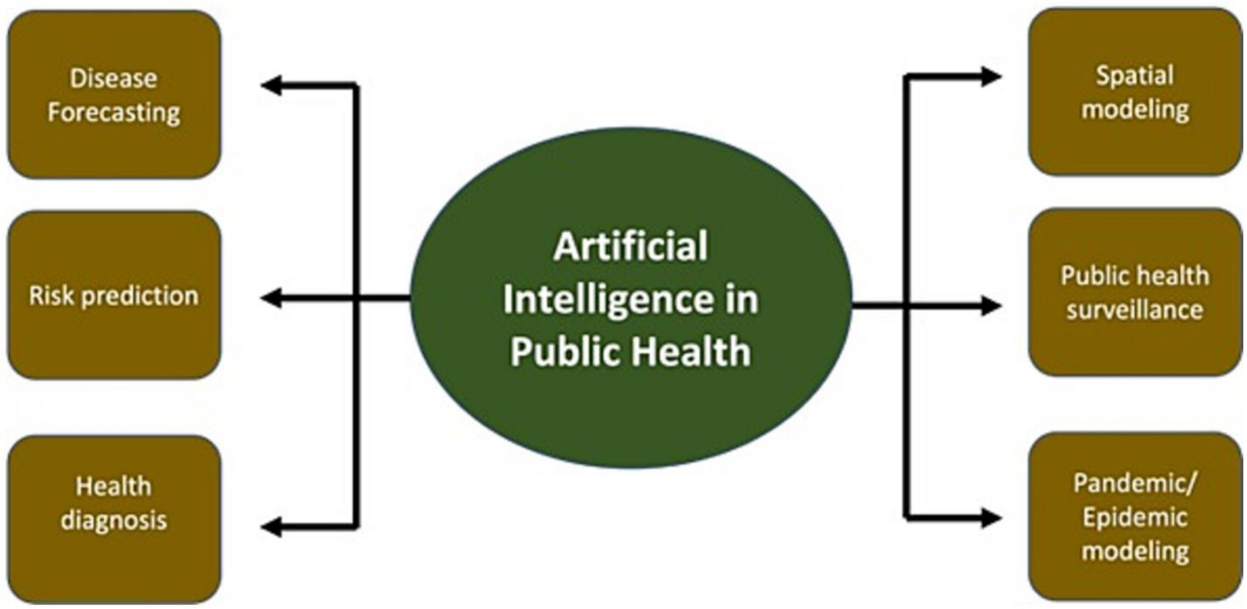

Figure 1 Artificial Intelligence in Public Health[3]

1.2 The Imperative for Effective Containment Measures

The challenge to grab the spread of Novel Virus and to mitigate its impact on public health cannot be overstated. The measures which range from social distancing and lockdown to testing and tracing, have been of significance importance to manage the crises. [4] However, the success of these protective measures is directly linked to the availability of accurate and timely information, adaptive strategies, and the ability to anticipate the trajectory and patterns of the pandemic. Here, the integration of artificial intelligence (AI) and machine learning (ML) emerges as crucial tools in effectively managing the pandemic. These technologies offer the capability to analyze vast amounts of data, identify trends, and provide insights that aid in decision-making and resource allocation. By harnessing the power of AI and ML, healthcare systems and policymakers can enhance their response efforts, optimize resource utilization, and ultimately curb the spread of the virus more effectively. Therefore, integrating AI and ML into containment strategies represents a critical step towards achieving greater success in combating the novel virus pandemic. [5]

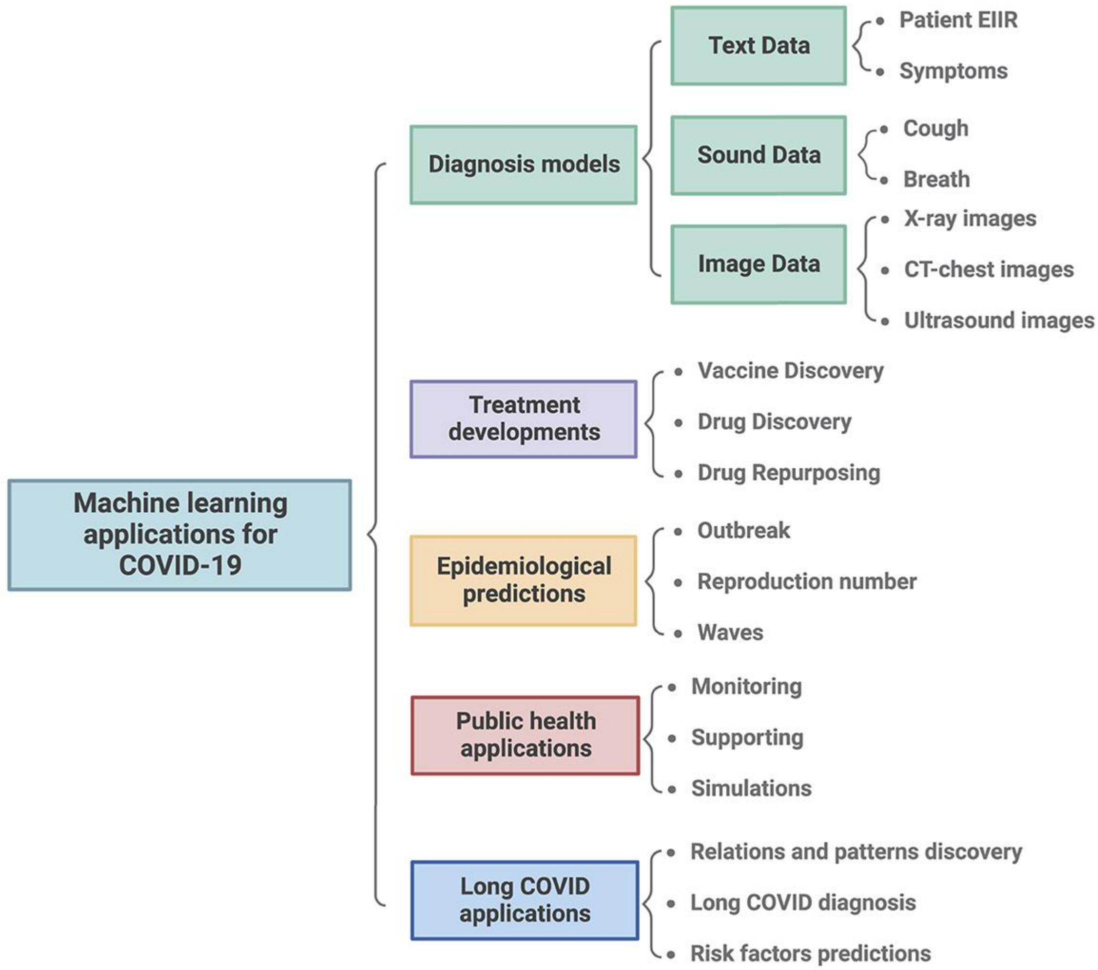

Figure 2 Machine Learning in COVID-19

1.3 AI and ML in Healthcare

The integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies into healthcare systems has heralded a new era of innovation and advancement in the field of medicine. These technologies offer a multitude of benefits that extend beyond their traditional role in data analysis. By harnessing the power of AI and ML, healthcare providers can achieve more accurate and timely disease detection, leading to improved patient outcomes and more efficient healthcare delivery. However, alongside the promise of these technologies come significant challenges and ethical considerations. The vast amounts of sensitive patient data involved raise concerns regarding data privacy and security, necessitating careful attention to safeguard patient confidentiality and compliance with regulatory standards. Furthermore, the potential for algorithmic bias and the need for ongoing education and training for healthcare professionals pose additional hurdles to the seamless integration of AI and ML into clinical practice. Despite these challenges, the transformative potential of AI and ML in revolutionizing healthcare delivery cannot be overstated. Addressing these concerns and ensuring the responsible and ethical deployment of AI and ML technologies is paramount to realizing their full potential in shaping the future of healthcare. In health care AI and ML have the following concerns. [6]

- **Medical Imaging and Diagnostics**:

Technology accurately shows the interpretation of medical images which assist radiologists and pathologists to identify abnormalities. [7] The pattern of disease prognosis, these technologies also help in early detection of tumors by X-Rays, MRI's and CT scans which helps in more precise diagnostics. [8,9]

- **Personalized Medicine:**

The analysis of genes by AI and ML helps healthcare professionals to detect vast genomic databases and identifies correlations and patterns of individual's response to treatment to make a suitable treatment plan. Maximum efficiency and minimum adverse effects could be achieved by this approach. [9]

- **Drug Discovery and Development**:

Technology is so innovative that it expedites the discovery of drug by compound screening and target identification. ML identifies biological data to identify potential drug targets, acceleration and early stages of drug development, which results in cost-effectiveness in bringing new drugs to the market. [10]

- **Global Collaboration and Data Sharing:**

AI facilitates global collaboration by enabling the sharing of data and insights across borders, fostering collaboration between researchers, healthcare professionals, and policymakers to combat infectious diseases on a global scale. [9]

- **Contact Tracing and Case Management**:

AI and ML algorithms support contact tracing efforts by analyzing contact networks, identifying high-risk individuals, and prioritizing testing and quarantine measures. These technologies enhance the efficiency and effectiveness of contact tracing programs, helping to control the spread of infectious diseases. [9]

- **Genomic Medicine**:

AI and ML techniques analyze genomic data to identify genetic variations associated with disease susceptibility, drug response, and treatment outcomes, guiding personalized medicine. approaches, and improving treatment efficacy. [9]

- **Telemedicine and Remote Monitoring**:

AI-driven telemedicine platforms and remote monitoring devices enable remote consultations, continuous patient monitoring, and timely interventions, expanding access to healthcare services. and improving patients' engagement. [9]

- **Continuous Learning and Improvement**:

ML algorithms continuously learn from new data and feedback, enabling iterative improvements in disease surveillance, diagnostic accuracy, treatment efficacy, and overall public health response to infectious diseases. [9]

- **Predictive Analytics and Risk Stratification:**

ML and AI also help in prediction of disease so that it can be treated in its early stage and to refrain from adverse side effects. This helps the healthcare team to take the proactive approach in interventions, care plans and allocate resources more efficiently and effectively based on risk assessment with the help of advanced technologies. [11]

- **Clinical Decision Support**:

By analyzing patient's data AI provides real-time clinical decisions by medical literature and treatment guidelines provided on various databases. The algorithms of ML help healthcare providers in making informed decisions by offering insight into diagnosis, treatment options and patient care. This ensures evidence-based decision making practice to treatment patient with latest medical knowledge and technology. [12]

- **Natural Language Processing (NLP):**

Another interesting feature of artificial intelligence is Natural Language Processing, which plays a vital role in transforming unstructured clinical notes within Electronic Health Records (EHR's) into valuable insights. It also allows hands-free access to information, improving workflow efficiency and facilitating easier communication. However, the devices combined with AI and ML allows continuous monitoring. These technologies detect anomalies and deviations from normal patterns.

Furthermore, AI and ML were helpful in many other ways like public health policy and decision making which depicts that AI helped policymakers by stimulating various scenarios and predictions about potential outcomes of different interventions in treating the symptoms of COVID-19. This all helped in making informed decisions about social distancing, vaccinations and lockdown. [13]

The major concern during COVID-19 was to makes sure that everyone is vaccinated, this could not be achieved without the integration of AI and ML, which needed identification of high-risk population, and ensure efficient allocation, therefore AI helped to streamline the vulnerable groups. [14]

As it is well known that Corona Virus has many variants, so ML algorithms analyze genomic data to monitor the emergence and spread of new variant of virus. This information is very much important for adapting public health strategies and making effective vaccine against evolving strains. This also helped in analyzing existing drug data base to identify potential candidates for repurposing the treatment of COVID-19. This helps healthcare professionals in treating the symptoms of COVID-19 by drugs which could be more effective against the deadly virus. [15]

1.4 Public health and COVID-19

Public health is the top notch concern of healthcare professionals and in this era of science and technology, the objectives of public health could not be achieved without the involvement of artificial intelligence and machine learning. Safety is of prime importance and AI models analyze behavioral data to predict public health adherence to safety guidelines. This help to stop potential outbreaks to avoid the spread of virus and implement safety measures. [16]

Another very important use of AI is in supply chain and logistics, as it was the pandemic and the globe has to cope up with the deadly virus. As the vaccines, drugs and all surgical and non-surgical items were supplied from one part of the world to another, so supply chain needs to be efficient like to maintain the cold chain of vaccine and much more, this could not be possible without AI on such a large scale. All critical supplies and avoiding shortages were ensured with AI. [17]

As COVID-19 was deadly, it not only affected the physiology but also the mental health of patients, because of quarantine for longer days, the social life was totally ended and loneliness during the disease caused anxiety stress and depression. AI also intervened in this aspect of health by monitoring and providing support for mental health by AI friendly applications. Furthermore, AI and ML also streamlined diverse data bases like clinical records and epidemiological information.

Research has a prime importance in healthcare as evidence based practice cannot be assured by the lack of researches in healthcare. AI also favors in this regard by facilitating global collaboration in research, where researchers share insights, pool resources and find out new ways of treatment and preventive measures. [18]

ML models used in various applications continuously learn from new data and real-world outcomes. Theoretical foundation of machine learning is based on supervised learning which involves training a model on labeled data, where each example is paired with a corresponding target variable or outcome. The model learns to generalize from the training data to make predictions on unseen data, aiming to minimize prediction errors. Common supervised learning algorithms include linear regression, logistic regression, decision trees, support vector machines, and neural networks and unsupervised learning deals with unlabeled data and seeks to uncover underlying patterns or structures within the data without explicit guidance. Clustering algorithms, such as k-means clustering and hierarchical clustering, group similar data points together based on their intrinsic properties. Dimensionality reduction techniques like principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) aid in visualizing high-dimensional data and extracting meaningful features, furthermore.

Reinforcement learning is a paradigm where an agent learns to interact with an environment to achieve a specific goal through trial and error. The agent receives feedback or rewards based on its actions, allowing it to learn optimal decision-making strategies over time.

This adaptability allows the refinement of models over time, improving their accuracy and effectiveness as the understanding of the virus evolves. However, the integration of AI and ML in addressing the multifaceted challenges of the COVID-19 pandemic reflects the adaptability and transformative potential of these technologies in healthcare and public health. Ongoing research and innovation in AI and ML continue to contribute to more effective responses to the evolving nature of the pandemic. [19]

In the realm of COVID-19 pandemic management, various predictive models have been employed to navigate the complexities of the virus's spread and impact. SEIR models, categorizing populations into Susceptible, Exposed, Infectious, and Recovered compartments, have been fundamental in simulating the dynamics of the disease, estimating peak infection rates, and evaluating the effectiveness of interventions. Machine learning algorithms, ranging from decision trees to neural networks, have played a pivotal role in analyzing intricate datasets for predicting virus spread, identifying high-risk populations, and optimizing resource allocation. Agent-based models, simulating individual interactions within populations, offer insights into the impact of individual behaviors on transmission dynamics and intervention effectiveness. Epidemic forecasting models integrate diverse data sources to provide actionable insights for policymakers, healthcare professionals, and the public regarding the trajectory of the pandemic. Additionally, healthcare resource allocation models and vaccine distribution models contribute significantly to optimizing resource deployment and vaccination strategies. [20] These models collectively serve as crucial tools, continually refined with real-time data, aiding researchers and public health officials in making informed, evidence-based decisions to effectively combat the COVID-19 pandemic.

1.5 Prediction models

The prediction models have been very helpful during COVID-19 as in navigating the complexities of virus, these models leverage advanced analytics and machine learning and play a pivotal role in forecasting the trajectory of virus, resource allocation and public health strategies. Regarding epidemiological forecasting, these models help in identifying spread, peaks on epidemiological curve and enable interventions. Furthermore, prediction models help in optimizing healthcare resources, guiding decisions on hospital beds, ventilators, medicines. [21]

Figure 3 Predictive Analytics and Artificial Intelligence

Prediction models employed to optimize vaccination strategies, predicting demand and identifying priority populations for effective distribution. In the realm of infection control, the effectiveness of interventions, such as social distancing measures, has been assessed through predictive modeling, guiding policymakers in implementing evidence-based measures. Moreover, these models have contributed to identifying high-risk patients, anticipating mental health challenges, and tracking the emergence of new virus variants. Overall, prediction models have proven indispensable in guiding decision-makers, healthcare professionals, and public health officials in their efforts to manage and mitigate the impact of the COVID-19 pandemic. [22]

Additionally, the adaptability of prediction models has been evident in their ability to evolve alongside the emergence of new virus variants, aiding in the continuous assessment of their impact on transmission dynamics and vaccine effectiveness. Despite the significant advancements in predictive modeling for disease surveillance and forecasting, several challenges persist. Data quality issues, including incompleteness, inaccuracies, and biases, pose significant challenges to the reliability and generalizability of predictive models. Model validation and evaluation techniques need to be robust and transparent to ensure the credibility and reproducibility of findings. Additionally, scalability concerns arise when applying predictive models to large and heterogeneous datasets, requiring efficient computational algorithms and infrastructure. Addressing these challenges requires interdisciplinary collaboration, methodological innovations, and ongoing research efforts to advance the field of predictive modeling in public health. However, addressing challenges such as data quality issues, model validation, and scalability concerns is essential to ensure the reliability and effectiveness of predictive models in safeguarding public health. [23]

RATIONALE OF THE STUDY

This systematic review aims to critically examine the landscape of prediction models employing AI and ML in the context of COVID-19 containment. The rationale stems from the urgency to assess the effectiveness, limitations, and potential contributions of these innovative technologies in guiding evidence-based public health interventions. [24] Understanding the extent to which AI and ML can augment traditional methods is paramount for enhancing preparedness, responsiveness, and resilience in the face of the ongoing pandemic and future health crises.

THE OBJECTIVE OF THESIS

1.To synthesize existing literature on the application of AI and ML in predicting and containing the spread of COVID-19.

2.. To evaluating the types of models utilized, assessing their effectiveness in guiding public health containment measures.

3. To Provide evidence-based recommendations for policymakers on the timing, duration, and optimal combination of interventions for effective containment of COVID-19.

LITERATURE REVIEW

The success of AI and ML depends on the quality and diversity of data inputs, so literature review is of prime importance for evidence based practice. This pin points the importance of real time and heterogeneous datasets. There are also some hurdles including the data privacy concerns, data bias and the need for standardized reporting. [25]

The critical aspect of any predicted model is its generalizability and validation. This systematic review tries to find out the methodologies employed by researchers to validate AI and ML for COVID-19 containment measures. The literature shows the results to be generalized on population. [26]

Ethical Implications and Considerations:

The ethical dimensions of deploying AI and ML models in public health were explored in the literature. Issues such as algorithmic bias, transparency, accountability, and the equitable distribution of resources are examined to provide a comprehensive understanding of the ethical landscape surrounding predictive modeling in the context of COVID-19. This literature review consolidates current knowledge on AI and ML models predicting the outcomes of public health containment measures for COVID-19. By synthesizing findings from diverse studies, the review aims to inform future research directions, guide the development of more robust models, and contribute to evidence-based decision-making in public health crises. [27,28]

Integration of Predictive Models into Decision-Making:

Examining the intricate relationship between predictive models and decision-making within the realm of public health. By exploring the integration of artificial intelligence (AI) and machine learning (ML) models into various aspects of decision-making processes, such as policy formulation, resource allocation, and strategic planning, the study aims to uncover the extent to which these advanced technologies have been adopted and utilized. Through a comprehensive analysis of practical applications, the research sheds light on how predictive models contribute to shaping decision outcomes in public health initiatives. By examining case studies and real-world implementations, it provides valuable insights into the effectiveness and impact of AI and ML models on improving decision-making processes and ultimately advancing public health agendas. The research serves as a bridge between theoretical frameworks and practical implementations, offering valuable perspectives on the challenges, opportunities, and best practices associated with integrating predictive models into decision-making processes within the public health sector. By synthesizing existing knowledge and highlighting emerging trends, it aims to inform policymakers, healthcare professionals, and researchers about the potential benefits and limitations of leveraging AI and ML technologies in shaping the future of public health strategies. [29]

Comparative Analysis of Model Performance:

Comparing the performance of different AI and ML models becomes essential to identify the most effective approaches. This research embarks on a thorough investigation of studies that have conducted such comparative analyses, delving deeply into key factors such as prediction accuracy, sensitivity, specificity, and computational efficiency. By meticulously examining the strengths and limitations inherent in various models, this study aims to provide nuanced insights that can inform the refinement and selection of optimal strategies for tackling diverse problems within the realm of AI and ML. Additionally, this analysis may shed light on emerging trends, methodological innovations, and areas for further research, thereby contributing to the advancement of knowledge in this rapidly evolving field. [30]

Long-Term Implications and Adaptability:

The durability and adaptability of predictive models are explored in this section. Given the dynamic nature of the COVID-19 pandemic, understanding how models evolve over time and their ability to adjust to novel challenges such as the emergence of new variants, shifts in public behaviors, and the introduction of innovative medical interventions. This exploration is vital for ensuring the continued efficacy of predictive models in informing public health strategies amidst the evolving nature of the pandemic. Changing public behaviors, and emerging medical interventions is crucial for sustained effectiveness. [31]

Public Perception and Acceptance:

The acceptance and trust of the general public in AI and ML-based predictive models play a pivotal role in their success. This section delves into studies that investigate public attitudes towards these technologies, addressing concerns, misconceptions, and ways to enhance transparency and communication for fostering greater public acceptance. [32] The literature review emphasizes the evolving landscape of AI and ML in predicting outcomes related to COVID-19 containment measures, underscores the need for ongoing research to address emerging challenges, and advocates for a collaborative and interdisciplinary approach to maximize the potential of these technologies in safeguarding public health. The synthesis of knowledge presented in this comprehensive literature review aims to contribute to the ongoing discourse on the application of AI and ML in public health, with specific relevance to the COVID-19 pandemic.

Global Perspectives on AI and ML in Public Health:

Examining the international landscape of AI and ML applications in public health, The literature explores the global landscape of artificial intelligence (AI) and machine learning (ML) applications in the realm of public health. By examining how various countries and regions have embraced and customized predictive models, it offers insights into the international adoption and adaptation of these technologies. Through comparative analyses, the literature elucidates variations in approaches, successes, and challenges encountered across different geographical contexts. This comprehensive exploration aims to provide a nuanced understanding of the global impact of AI and ML on COVID-19 containment measures, highlighting both best practices and areas for improvement. By synthesizing findings from diverse regions, this research contributes to the development of a more cohesive and effective global response to public health challenges leveraging AI and ML technologies. [33]

Impact of Socio-Economic Factors on Model Effectiveness:

Socio-economic factors, such as income disparities, education levels, and access to healthcare, can significantly influence the effectiveness of public health containment measures. This section explores how AI and ML models account for and address these factors, acknowledging the importance of tailoring predictive models to the unique challenges faced by diverse communities.

Innovative Data Sources and Integration Methods:

The importance of diverse and innovative data sources, it explores emerging data streams and integration methods used to enhance the predictive capabilities of AI/ML models for COVID-19 containment and discusses the integration of non-traditional data sources, such as social media, wearable devices, and environmental sensors, into predictive modeling frameworks. [36]

Lessons Learned from Previous Pandemics:

Drawing lessons from the application of AI and ML in previous pandemics (e.g., SARS, H1N1), the literature provides insights into the historical context of utilizing predictive models for infectious disease control. Analyzing successes and failures from past experiences informs the development of more resilient and adaptive models for the current and future pandemics. [34]

Longitudinal Studies and Temporal Analysis:

Focusing on the temporal dimension of predictive modeling, this heading examines longitudinal studies and temporal analysis techniques employed to track the evolution of COVID-19 outbreaks over time. It explores how AI/ML models can capture temporal trends, seasonality patterns, and evolving transmission dynamics to inform dynamic public health interventions. [33]

Regulatory and Policy Implications:

The integration of AI and ML in public health practices raises regulatory and policy considerations. The literature shows existing frameworks and policies governing the deployment of predictive models, emphasizing the need for ethical guidelines, standards, and oversight to ensure responsible and equitable use of these technologies in the context of COVID-19. [34]

Collaborative Initiatives and Partnerships:

The collaborative nature of addressing public health challenges is highlighted by literature, exploring collaborative initiatives between governments, research institutions, industry partners, and international organizations, the review underscores the collective effort required to harness the full potential of AI and ML in optimizing COVID-19 containment measures.

However, Synthesizing the extensive literature, this literature provides a holistic perspective on the multifaceted role of AI and ML in predicting outcomes related to COVID-19 containment measures. It underscores the need for a nuanced and context-specific approach, continuous learning from global experiences, and the importance of ethical, collaborative, and human-centric considerations in shaping the future of predictive modeling in public health crises. [35]

Addressing Health Disparities and Vulnerable Populations:

The literature shows how AI and ML models can be tailored to address health disparities and vulnerabilities within specific populations. Analyzing studies that focus on inclusivity and equitable access to healthcare resources, the review examines strategies to ensure that predictive models contribute to reducing disparities in the impact of COVID-19 containment measures [29]

Integration of Environmental Factors and Climate Data:

Environmental factors and climate data play a crucial role in understanding the transmission dynamics of infectious diseases. This section investigates the incorporation of environmental variables into AI and ML models, highlighting studies that leverage climate data to enhance the accuracy and predictive power of models aimed at optimizing COVID-19 containment strategies. [18]

Hybrid Approaches: Integrating AI with Traditional Epidemiological Models:

Hybrid models that combine the strengths of AI with traditional epidemiological models offer a promising avenue for enhancing predictive accuracy. This section examines studies that explore the synergies between AI techniques and established epidemiological methods, providing insights into the potential benefits and challenges associated with hybrid modeling approaches. [23]

Impact of Vaccination Campaigns on Predictive Models:

The global rollout of COVID-19 vaccines has introduced a new dimension to containment measures. The literature depicts how AI and ML models have been adapted to assess the impact of vaccination campaigns on transmission rates, herd immunity, and the overall effectiveness of public health interventions. [9]

Post-Pandemic Preparedness:

Looking beyond the immediate challenges of the COVID-19 pandemic, the literature depicts the implications of AI and ML models for post-pandemic preparedness. Examining studies that propose frameworks for building resilient public health systems, the review provides insights into how predictive modeling can contribute to long-term preparedness strategies. [13]

The literature review provides a nuanced understanding of the evolving landscape of AI and ML in predicting outcomes related to COVID-19 containment measures. By exploring a diverse array of topics, from addressing health disparities to cybersecurity considerations, the review contributes to a holistic understanding of the challenges, opportunities, and future directions in leveraging advanced technologies for public health crises. This synthesis aims to guide researchers, policymakers, and practitioners in harnessing the full potential of AI and ML to inform evidence-based decision-making and enhance the effectiveness of public health interventions. [28]

MATERIALS AND METHODS

2.1. Search Strategy

The search strategy employed for this systematic review aimed to comprehensively identify relevant studies pertaining to the application of AI and ML in predicting outcomes related to COVID-19 containment measures. The strategy followed a systematic approach, utilizing multiple databases and search engines to ensure a thorough exploration of the literature landscape. Firstly, several key databases were systematically searched, including Nursing Reference Center Plus, CHINAHL, Scopus, PubMed, and Living Evidence. These databases were selected based on their comprehensive coverage of healthcare, medical, and interdisciplinary research literature. The search was conducted from February 1, 2019, to September 2023, spanning a period that encompassed the initial phases of the COVID-19 pandemic and its subsequent evolution. This timeframe was chosen to capture a wide range of studies published during the emergence and spread of COVID-19, as well as ongoing research conducted to address the evolving challenges posed by the pandemic. The search strategy was designed to be inclusive, with no restrictions placed on language or publication status. This approach ensured that all relevant studies, including preprints and updates reassessed after journal publication, were considered for inclusion in the review. By casting a wide net and encompassing studies from diverse linguistic and publication backgrounds, the search strategy aimed to minimize potential biases and ensure a comprehensive synthesis of the available evidence.

The search strategy employed a systematic approach to identify relevant studies from diverse databases. Using a combination of keywords, phrases, and controlled vocabulary terms, including but not limited to "COVID-19," "Coronavirus," "SARS-CoV-2," "Artificial Intelligence," "Machine Learning," "Predictive Modeling," "Disease Surveillance," "Forecasting," and "Public Health," comprehensive search queries were formulated. These terms were combined using Boolean operators (e.g., AND, OR) and truncation symbols (e.g., *) to capture a wide range of relevant literature. Specific Medical Subject Headings (MeSH) terms related to COVID-19 and predictive modeling were also incorporated to further refine the search results and ensure relevance. Additionally, terms related to study design (e.g., "predictive modeling," "meta-analysis," "systematic review") and population characteristics (e.g., "public health professionals," "healthcare workers") were included to target studies of interest.

Overall, the search strategy adopted for this systematic review reflects a rigorous and systematic approach to identifying relevant literature on the application of AI and ML in predicting outcomes related to COVID-19 containment measures.

2.2. Inclusion Criteria

The inclusion criteria were defined to encompass studies utilizing Artificial Intelligence (AI) and/or Machine Learning (ML) methodologies for the development or validation of public health interventions and their associated outcomes. Titles, abstracts, and full texts of identified articles were subject to a rigorous screening process performed independently by reviewers (A.B.P., D.C., D.S. S.T). Discrepancies in eligibility assessments were resolved through thorough discussion involving the expertise of M.P. and K.V.

2.3. Study Selection Process

The study selection process involved a hierarchical approach. Initially, titles were screened to exclude irrelevant studies. Subsequently, abstracts were evaluated for relevance, and finally, full texts were scrutinized against the inclusion criteria. Duplicate screening by independent reviewers enhanced the reliability of the study selection process. Any disagreements between reviewers were resolved through discussion, consulting the expertise of senior reviewers (M.P., K.V.).

2.4. Data Extraction

Relevant data from included studies were systematically extracted using a predefined template. Information pertaining to study characteristics, AI/ML techniques employed, public health interventions studied, and key outcomes was collected. This structured approach to data extraction aimed at ensuring consistency and completeness of information across all included studies.

2.5. Definition of Interventions

Quarantine:

Quarantine refers to the practice of isolating individuals who have been exposed to COVID-19, either because they have tested positive for the virus or because they have been in close contact with someone who has tested positive. Quarantine aims to prevent further transmission of the virus by keeping potentially infected individuals away from others. During quarantine, individuals are typically required to stay at home or in designated quarantine facilities for a specific period, usually 10 to 14 days, to monitor for symptoms and prevent potential spread to others. [20]

Full Lockdown:

A full lockdown is a comprehensive containment strategy implemented by governments to minimize contact between individuals and curb the spread of COVID-19. During a full lockdown, stringent measures are put in place to restrict movement and activities in the community. This may include shutting down government departments, businesses, schools, social and leisure facilities, and transportation services, with only essential services such as healthcare, emergency services, and basic utilities remaining operational. The goal of a full lockdown is to reduce the transmission of the virus by limiting social interactions and preventing gatherings of people in public spaces. [20]

Partial Lockdown:

A partial lockdown is a modified version of a full lockdown that takes into account the spatial risk of COVID-19 transmission in different areas. Instead of implementing uniform restrictions across the entire region, a partial lockdown allows for varying levels of containment measures based on the degree of risk posed by the spread of the disease. This approach involves continuously monitoring key parameters, such as infection rates, hospitalizations, and positivity rates, to assess the level of risk in different areas and adjust lockdown restrictions accordingly. Areas with lower risk may have fewer restrictions, while areas with higher risk may implement more stringent measures. By tailoring lockdown measures to the specific risk level of each area, a partial lockdown aims to balance the need to control the spread of the virus with minimizing the social and economic impact on communities. [21]

Social Distancing:

Social distancing is a preventive measure aimed at reducing the transmission of COVID-19 by minimizing close contact between individuals. It involves maintaining physical distance of at least 2 meters (or about 6 feet) from others outside of one's household. This includes avoiding crowded places, large gatherings, and close contact with people who are not part of one's immediate family or social bubble. Social distancing measures also include practicing good hygiene habits, such as frequent handwashing, wearing face masks in public settings, and covering coughs and sneezes with a tissue or elbow. By limiting close contact between individuals, social distancing helps to reduce the risk of virus transmission and flatten the curve of infection, ultimately slowing the spread of COVID-19 within communities. [20]

2.6. Quality Assessment

The methodological quality of included studies was assessed to gauge the robustness of their designs and methodologies. Quality assessment criteria were predefined, and evaluations were conducted independently by reviewers. Any discrepancies were resolved through discussion and, if necessary, consultation with senior reviewers.

2.7. Synthesis and Analysis

A qualitative synthesis of the findings was conducted to provide a narrative overview of the key themes, methodologies, and outcomes across the included studies. Quantitative analyses, such as meta-analyses or subgroup analyses, were planned based on the homogeneity of the included studies. Sensitivity analyses were considered to assess the impact of study quality on overall findings.

2.8. Ethical Considerations

This review adhered to ethical standards and guidelines for systematic reviews. No individual patient data were used, ensuring privacy and confidentiality. Ethical approval was not required as the study involved the synthesis and analysis of publicly available data.

The robustness of the search strategy, inclusion criteria, and analysis methods collectively aimed at ensuring a comprehensive and systematic review of studies utilizing AI and/or ML for public health interventions related to COVID-19.

2.9. Addressing Potential Bias

To mitigate potential bias, the search strategy encompassed multiple databases, minimizing the risk of overlooking relevant studies. Inclusion criteria were applied rigorously, and any disagreements during the screening process were resolved through consensus. The comprehensive nature of the search, including studies in different languages and publication statuses, aimed to reduce publication bias.

2.10. Handling of Preprints

Preprints, including updates reassessed after journal publication, were considered to ensure the inclusion of the latest advancements in AI and ML applications for public health interventions related to COVID-19. The decision to include preprints was made to capture timely information and innovation while acknowledging the importance of subsequent peer review for validation.

2.11. Continuous Monitoring for Living Evidence Updates

Given the dynamic nature of the Living Evidence platform, continuous monitoring was employed to capture updates on COVID-19 studies. This allowed the inclusion of the most recent research findings and ensured that the synthesized information reflected the evolving landscape of AI and ML applications in the context of public health interventions.

2.12. Inter-Rater Reliability

Inter-rater reliability was enhanced through the involvement of multiple independent reviewers in the screening and selection process. The inclusion of a third-party arbitrator (M.P., S.T.) in cases of reviewer discrepancies provided an additional layer of objectivity, contributing to the overall reliability of the study selection process.

2.13. Transparency and Reporting

The systematic review adhered to established reporting guidelines (e.g., PRISMA) to ensure transparency and completeness in reporting the review process and findings. This approach facilitated the reproducibility of the study, enabling readers to assess the reliability and validity of the review methods.

2.14. Limitations and Potential Biases Acknowledgment

The limitations and potential biases of the included studies and the systematic review process were acknowledged. Variability in study designs, methodologies, and the evolving nature of the COVID-19 pandemic posed inherent challenges. The review aimed to transparently communicate these limitations to provide a balanced interpretation of the findings.

2.15. Stakeholder Involvement

Stakeholder involvement was considered, including input from public health professionals, AI/ML experts, and policymakers. While not directly involved in the review process, potential implications of the findings for these stakeholders were contemplated to ensure the relevance and applicability of the synthesized evidence.

2.16. Reporting of Funding Sources

Transparency in reporting funding sources was prioritized. Any financial support or conflicts of interest associated with the included studies were documented and reported. This approach aimed to enhance the credibility of the review by providing insight into potential influences on the reported outcomes.

The detailed consideration of these methodological aspects aimed to strengthen the systematic review's validity, reliability, and applicability, ensuring a comprehensive and objective synthesis of studies utilizing AI and/or ML for public health interventions related to COVID-19.

RESULTS

We found and retrieved 3041 articles. After the removal of 14 duplicate records, 3027 articles were retained for screening. After the screening, 2943 records were excluded, and 84 full-text articles were assessed for eligibility. After the assessment, 76 full texts were excluded, and twelve (12) studies met the inclusion criteria and were included in the qualitative synthesis.

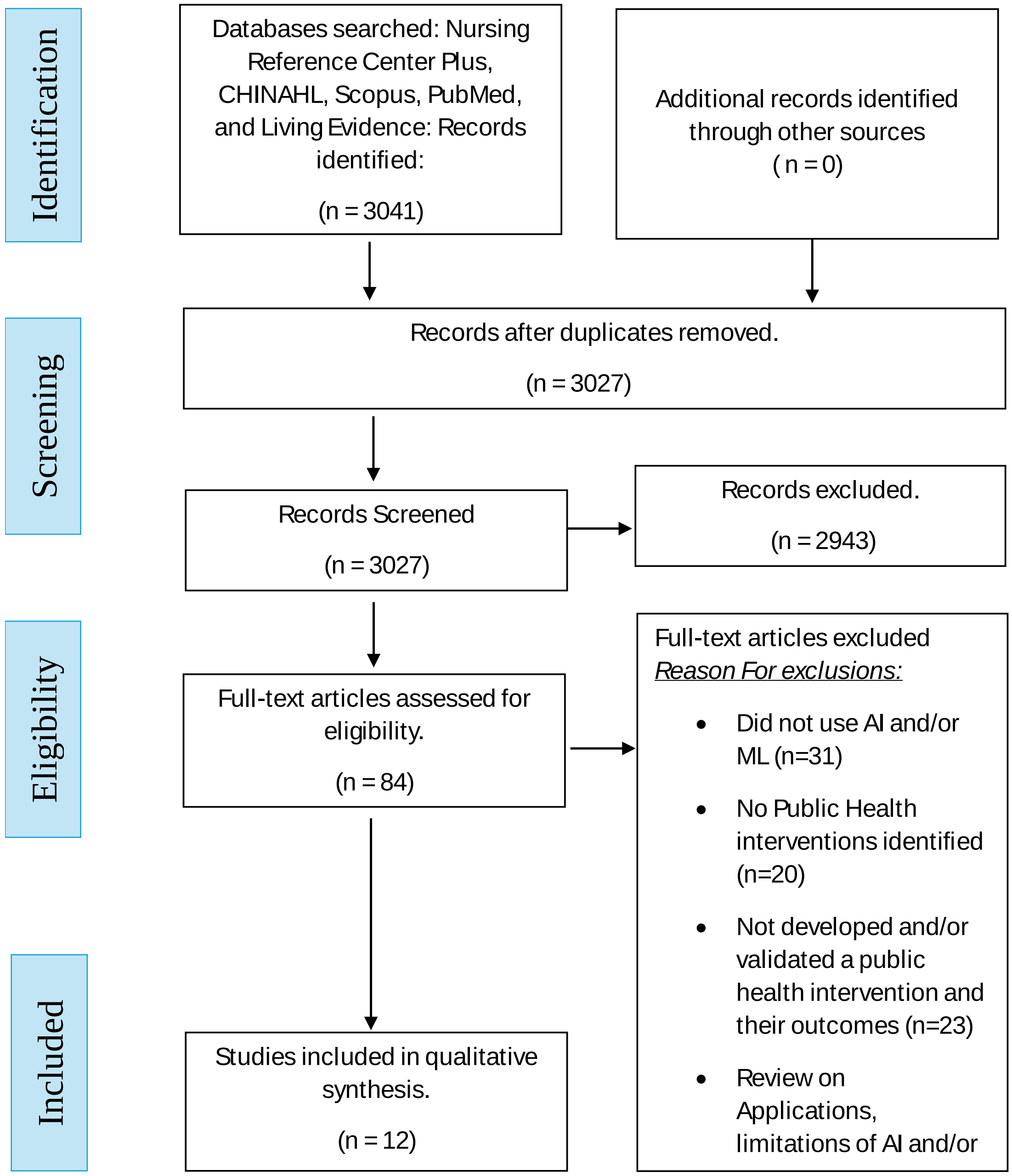

Figure 4 PRISMA Flow Diagram for the selection of articles.

In Table 1, the study characteristics are described. Nine (9) studies used data from a single nation. Three (3) studies used data from multiple countries.

Table 1: Types of models and typology of data, and their setting in the included studies.

Title	Author	Setting	Outcome	Model development	Model characteristic	Typology of data
On the Spread of Coronavirus Infection. A Mechanistic Model to Rate strategies for Disease Management.	Shiyan Wang	United States	Control of the epidemic spread, reduce spike	New	Mechanistic	Empirical
No Place Like Home: Cross-National Data Analysis of the Efficacy of Social Distancing During the COVID-19 Pandemic.	Dursun Delen	26 countries	Control of the epidemic spread, reduce spike.	Existing	Susceptible–infected–recovered (SIR)	Empirical
Predicting the COVID-19 positive cases in India with concern to Lockdown by using Mathematical and	Ajit Kumar Pasayat	India	Control of the epidemic spread, reduce spike.	Existing	Exponential Growth, Linear Regression	Simulation

Machine Learning based models.						
Preparedness and Mitigation by projecting the risk against COVID-19 transmission using Machine Learning Techniques.	Akshay Kumar	India	Risk of hotspot formation	New	Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)	Simulation
Quantifying the effect of quarantine control in COVID-19 infectious spread using machine learning.	Raj Dandekar	Wuhan, Italy, South Korea, USA	Control of epidemic spread	New	Neutral network augmented.	Empirical
COVID-19 Epidemic in Switzerland: Growth Prediction and Containment Strategy Using Artificial Intelligence and Big Data.	Marcello Marini	Switzerland	Outbreak prediction evolution of spread, rate of recovery	Existing	Agent-based simulation framework, EnerPol	Simulation
Impacts of Social and Economic Factors on	Yun Qiuy	China	Reduce the transmission rate	Existing	Empirical	Empirical

the Transmission of Coronavirus Disease 2019 (COVID-19) in China.						
Beware of asymptomatic transmission: Study on 2019-nCoV prevention and control measures based on extended SEIR model.	Peng Shao	China	Control of the epidemic spread	Existing	Susceptible–Exposed–Infectious–Recovered (SEIR)	Simulation
Data-Driven Deep Learning Neural Networks for Predicting the Number of Individuals Infected by COVID-19 Omicron Variant	Ebenezer O. Oluwasakin	Portugal, Italy, and China	The main outcome is the prediction of the daily and cumulative number of individuals infected with the COVID-19 Omicron variant	New/existing	SIR model reduced to a logistic differential equation. Rational and birational models Time-series model based on neural networks. Logistic-Informed Neural Network (LINN)	Empirical
Machine learning analysis of government'	Chunlan Guo	Wuhan, China	Control and Prevention of Epidemic	Existing	Latent Dirichlet Allocation (LDA)	Empirical

s public risk communication during COVID-19 lockdown in Wuhan, China						
City lockdown and nationwide intensive community screening are effective in controlling the COVID-19 epidemic: Analysis based on a modified SIR model	Tailai Peng	Wuhan, China	Control of the epidemic spread, reduce spike.	Existing	Modified SIR Susceptible-infected-recovered	Empirical
Analysis of the Effectiveness of Public Health Measures on COVID-19 Transmission	Thiago Christiano Silva	Brazilian cities	Reducing peak of COVID-19 cases	Combination of Existing	SIR Model VAR (vector autoregressive)	Empirical

Twelve studies presented in the table delve into the dynamics of COVID-19 transmission and management, each study is characterized by its unique objectives, location, model type, models used, and approach employing a mix of existing and novel methodologies. Among these Nine studies used existing models and three used new models. The first one performed In the United States, Shiyan Wang proposed a new mechanistic model aimed at evaluating strategies for managing the spread of coronavirus infections. Dursun Delen conducted a cross-national data analysis (26 countries) to evaluate the efficacy of social distancing interventions and analyzed the transmission rates of the disease over the course of 5 weeks [22]. Meanwhile, in India, Ajit Kumar Pasayat et al. combined mathematical (Exponential Growth) and ML (Linear Regression) models to predict the rates of COVID-19 cases in India with concern to lockdown.

intervention [24]. Akshay Kumar's study in India assesses the risk of hotspot formation using a new technique called Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) it is a decision-making method that evaluates alternatives based on their proximity to an ideal solution. Raj Dandekar augmented neural network models to project the risk against COVID-19 transmission in multiple countries. Marini et al. used EnerPol, a holistic agent-based model, to predict the growth of the epidemic according to containment strategy in Switzerland [25]. Qiu et al. adapted an empirical model that examined the role of various socioeconomic mediating factors, including public health measures encouraging social distancing in local communities, in reducing COVID-19 transmission. Peng Shao built a SEIR model (MATLAB R2017a) based on the movement of people across regions, revealing the effects of three public health measures on the control of the epidemic. Ebenezer O. Oluwasakin's study, conducted in Portugal, Italy, and China, aims to predict the number of individuals infected with the COVID-19 Omicron variant using a combination of existing models like the SIR model reduced to a logistic differential equation, rational and birational models, and time-series model based on neural networks in an empirical approach. Chunlan Guo's study in Wuhan, China, employs Latent Dirichlet Allocation (LDA) for controlling and preventing epidemic spread. LDA is a statistical model for topic modeling, revealing underlying themes in text data by assigning words to topics. It's used iteratively to analyze large text datasets and identify key patterns, aiding in effective epidemic management strategies. Peng's study in Wuhan, China, focuses on controlling epidemic spread and minimizing spikes using a modified Susceptible-Infected-Recovered (SIR) model. Peng's study likely introduces modifications to the traditional SIR model to better capture the dynamics of the specific epidemic in Wuhan. These modifications could involve incorporating additional factors such as population mobility, transmission rates, or interventions like vaccination or social distancing measures. Thiago Christiano Silva's study in Brazilian cities aims to mitigate the peak of COVID-19 cases by combining the traditional Susceptible-Infected-Recovered (SIR) model with a Vector Autoregressive (VAR) model. The SIR model is a standard epidemiological model used to understand the dynamics of infectious diseases, while VAR models are commonly employed in econometrics and time series analysis to capture relationships and dependencies between multiple variables over time. By integrating these two models, Silva seeks to enhance the understanding of COVID-19 transmission dynamics in Brazilian cities and develop effective strategies for reducing the peak of cases.

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Three studies used new models. Wang et al. proposed a new mechanistic model describing the transmission of COVID-19 in the United States [27]. Kumar et al. proposed a prospective methodology using TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). This consisted of the multi-criteria decision-making technique able to measure the spatial footprint of COVID-19 and to predict the epidemic spread analysis of the risk in a region at the beginning of the outbreak [21]. Dandekar et al. used mixed first principles epidemiological equations and data-driven neural network models to interpret and extrapolate from publicly available data the effect of quarantine interventions to control the epidemic in all the stages of outbreak [28].

About the outcomes, as it has been shown in Table 1, four models estimated the probability that a SARS-COV-2 outbreak could be controlled [22–24,28]. In the study performed by Wang et al., the outcomes included the reduction in the epidemic spike and the probability to avoid the second wave of the infection [27]. The other studies adopted outcomes such as forecasting the risk of new hotspot formation [21], the prediction of the outbreak evolution and the rate of recovery [25], and the reduction in the transmission rate [26].

In Table 2, the effectiveness of the interventions (single and multiple interventions) is described. In fact, interventions such as a stringent quarantine and a massive lockdown significantly reduced the transmission rate of COVID-19 and avoided more than 1.4 million infections and 56,000 deaths in China [26]. Another study showed that a partial lockdown had a strong impact on eventual infection fraction (x~(adjusted-$R2 = 0.59$, $p = 2 \times 10{-}6$)) and concluded that the lockdown should be implemented before the peak infection [27]. The models that used empirical data showed that quarantine was effective in controlling the epidemic spread also as a part of single and multiple interventions in all the stages of the outbreak [26–28]

Table 2 Effectiveness of interventions

Author	Outbreak phase	Intervention type	Description of intervention	Results
Shiyan Wang	All stages of epidemic	Multiple	1.stay at home order. 2. Easing social distancing measures. 3. Mandatory quarantine for travelers. 4. Non-essential business closure. 5. Gathering ban. 6.School closure. 7.Restaurant limits.	The study suggested that non-essential business closure, a gathering ban and school closure could have a strong impact on eventual infection fraction—if the interventions were implemented before the peak infection rate.
Dursun Delen	All stages of epidemic	Single	Social distancing	Social distancing policies could help in slowing the spread of COVID-19 (approximately 47% of the variation in the disease transmission rates) as well as in flattening the epidemic curve.
Ajit Kumar Pasayat	All stages of epidemic	Single	(i.) Lockdown is notcontinuing strictly after May 18th, 2020. (ii.) Lockdown continues.	Partial lockdown could play a positive role in preventing the spread of the disease.
Akshay Kumar	Beginning of the epidemic	Single	Adaption of lockdown measures	The study suggested to: (i) Release all

			according to the risk (low, moderate, and high) of new hot spots.	constraints except mass gatherings and travel out of district in low-risk areas. (ii) Release partial constraints, i.e., (i) + markets with essential commodities in moderate-risk areas. (iii) Seal the districts with essential commodities at doorsteps in high-risk areas.
Raj Dandekar	All the stages of epidemic	Single	Quarantine and isolation	Strong correlation between strengthening of the quarantine, actions taken by governments, and a decrease in effective reproductive number (Rt).
Marcello Marini	Beginning of the epidemic	Multiple	1.Closure of schools. 2.Closure of activities. 3.Limitation of public transport. 4.Social distancing.	The study estimated that, in the absence of interventions, 42.7% of the Swiss population would have been infected.
Yun Qiuy	Beginning of the epidemic	Multiple	1.stringent quarantine. 2.Massive lockdown.	The interventions significantly reduced the

			3.Other public health measures.	transmission rate of COVID-19. The study also demonstrated that the actual population flow from the outbreak source poses a higher risk to the destination than geographic proximity and similarity in economic conditions.
Peng Shao	Beginning of Epidemic	Multiple	1.Quarantine of infected people. 2.Reduction in movement of people.	The measures could help in controlling the spread of the epidemic.
Ebenezer O. Oluwasakin	Initial spread of the COVID-19 Omicron variant	Multiple	Analysis of social distancing, quarantine, and travel restrictions, in different countries. Assessment of mathematical models and deep learning algorithms in predicting the spread of the COVID-19 Omicron variant.	It suggests exploring the impact of various public health interventions and government policies on transmission rates to inform effective control strategies
Chunlan Guo	Beginning of the Epidemic	Multiple	Effective risk communication during the pandemic.	Government messages during Wuhan's lockdown boosted public resilience, but citizen

				engagement waned over time. Early interaction improved health communication during lockdowns.
Tailai Peng	Beginning of the Epidemic	Multiple	Lockdown Community Screening Social Distancing	The modified SIR model demonstrated that city lockdown and intensive community screening effectively suppressed the spread of COVID-19 in Wuhan and China excluding Hubei.
Thiago Christiano Silva	Beginning of Epidemic	Multiple	Social Isolation Mask Usage	Spectral network analysis suggests that implementing social isolation measures and promoting mask usage effectively lower the COVID-19 transmission rate in Brazil.

The studies listed in the table represent a comprehensive exploration of strategies aimed at mitigating the spread of COVID-19 across different geographical regions and stages of the epidemic. Utilizing a wide range of methodologies, from mechanistic models to cross-national data analyses and machine learning algorithms, researchers have meticulously examined the effectiveness of interventions such as social distancing measures, lockdowns, and quarantine protocols. These investigations reveal the intricate relationship between the implementation of interventions and the dynamics of the epidemic, shedding light on how such measures impact disease transmission rates and epidemic trajectories differently. By delving into transmission patterns and susceptibility factors, these studies emphasize the importance of adopting tailored approaches to address emerging hotspots and contain the spread of the virus effectively. Through the use of advanced technologies like artificial intelligence, big data analytics, and deep learning frameworks, researchers have employed predictive modeling to forecast disease trends and guide evidence-based decision-making. Social distancing policies that were implemented in 26 countries showed a reduction in disease transmission rates (47% variation) and were effective in flattening the curve [22].

The models that used AI and ML to simulate the effectiveness of intervention showed similar results. A mathematical and ML modeling study that simulated an intervention with lockdown measures concluded that the lockdown with certain restrictions might help in preventing the spread of the epidemic [24].

A model that simulated multiple interventions such as the closure of schools and activities, the limitation of public transport and the adoption of social distancing showed that without such interventions, 42.7% of the Swiss population would have been infected by 25 April 2020 compared with the observed 1% infection rate over the period [25]. A different approach was adopted by Kumar et al. and evaluated the effectiveness of lockdown according to the level of diffusion of the virus. In low-risk areas, the study showed that releasing all constraints except mass gatherings and traveling out of the district should be effective. In moderate-risk areas, releasing partial constraints except mass gatherings and travel out of the district and markets with essential commodities should be effective. In high-risk areas, lockdown should be increased, sealing the districts with essential commodities at doorsteps to be effective [21]. The adoption of quarantine of the people with infectious status (I-status) and reducing their movement could be effective in controlling the spread of the epidemic. This study also recommended that if medical resources are available, the exposed status (E-status) individuals or potential E-status individuals should be included in the scope of isolation and treatment. Moreover, the government should promptly release information on the epidemic situation and information on the areas and vehicles used by the infected people to further encourage those who have been in contact with individuals (I-status or E-status) to go to nearby hospitals for immediate inspection [23].

DISCUSSION

Based on our findings, quarantine emerged as the most effective intervention to control the spread of COVID-19 [23,26,28]. China implemented a combination of interventions based on quarantine that also included the implementation of cordon sanitary measures and traffic restrictions from 23 January 2020 to 16 February 2020. Before the implementation, the Rt was above 3.0. After the application of the quarantine, on 6 February 2020 the Rt decreased to below 1.0, and on 1 March 2020 the Rt decreased to less than 0.3 [29]. The data of 190 countries worldwide that implemented the quarantine measures (from 23 January 2020 to 13 April 2020) showed how they were associated with a reduction in Rt when compared with countries that did not adopt this measure (Rt = −11.40%, 95% CI (−9.07–−13.66%)) [30]. AI and ML were also applied in the use of lockdown [26]. The results of eleven European countries that implemented a lockdown between 3 February 2020 and 4 May 2020 showed a reduction in Rt below 1 and a large effect on reducing transmission [31]. A recent study that ranked the effectiveness of worldwide COVID-19 public health interventions that were implemented in 79 territories showed that curfews, cancellations of small gatherings and closures of schools, shop and restaurants were among the effective public health policies [32]. All these results were consistent with the outputs of the quarantine and lockdown-based AI and ML models [23,26–28]. AI and ML also simulated the adoption of continuously redefining the modification of lockdown measures according to the spatial (area) risk of the spread of the disease in one area (low, moderate, and high) [21]. This intervention was mainly used by Western European countries. Additionally, India implemented the same approach during lockdown phase 3 (from 4 May 2020 to 17 May 2020). After the application of this measure, the Rt decreased from 2.78 to 1.38. In brief, even though this approach reduced the spread of COVID-19 epidemic progression, it was unable to halt and eventually eradicate the COVID-19 epidemic [33]. Social distancing was the last strategy that was evaluated with AI and ML. AI and ML suggested that social distancing could be effective only in combination with the closure of schools/commercial activities and the limitation of public transportation [25]. Additionally, from real life data the application of social distancing as a single intervention was not very successful because case resurgence was likely to occur once it was removed and it did not help to reduce the excess mortality [34,35]. The models used in our study are quite diverse and a few considerations about their characteristics are worthwhile. The main models considered are the following: SIR/SEIR (Susceptible–Exposed–Infected–Recovered), Linear Regression, TOPSIS, Neural Networks, Agent-based Simulation.

These models are from very different families of methods, ranging from differential equation models (SIR/SEIR) to statistical machine learning models (linear regression and neural nets), geometric models (TOPSIS), and, finally, simulation models (agent-based simulation). A direct comparison is then hard, and the choice of one method with respect to another one may depend upon several factors, such as the kind of collected data, the availability of analytical tools, and the contextual situation under which the model can be applied. For instance, the SIR family of models, as any model in system theory (i.e., differential equations), assumes that the modeled system abstracts to some specific behavior. In standard SIR, a homogeneous mixing of the infected I and susceptible S populations is assumed, meaning that a person's contacts are randomly distributed among all others in the population. However, in real situations, the mixing in a population is heterogeneous and contacts are usually not random; for example, people of different ages may have very different kinds of relationships. Machine learning models do not assume such a kind of abstract behavior, since they try to predict specific patterns of prediction from data; in other words, they tend to learn the abstract behavior of the system from observations, and they use what has been learnt to make predictions. However, in this case specific modeling assumptions are also present. Standard linear regression is a model with very high bias, since it assumes a linear relationship between observed data and the target; however, the bias can be reduced by adjusting the model to polynomial regression with the introduction of additional nonlinear (quadratic, cubic, etc.) parameters. It is well-known that this bias reduction will increase the variance of the model, leading to the problem of overfitting (the inability of the model to generalize to unobserved data, while being really accurate on observed data). Regularization techniques (lasso or L2 regularization) can be adopted to reduce overfitting [36]. Neural networks are more general, since the non-linearity can be captured in the activation functions of the artificial neurons (usually sigmoid functions such as logistic or hyperbolic tangent, as well as Rectified Linear Unit widely adopted in deep neural net modes), and overfitting can be mitigated by both suitable architectural choices as well as regularization. However, the choice of the right set of hyper-parameters of the net (number of neurons, number of hidden layers, activation functions) and of the learning algorithm (learning rate, momentum, parameter initialization) may have a great impact on the final model's performance and must be made by intensive cross-validation procedures. Geometric models such as TOPSIS more directly address a decision-making process and are quite interesting in a setting like the one discussed in the present paper, i.e., the evaluation of specific countermeasures to contain the spread of COVID-19. TOPSIS belongs to the class of Multiple Attribute Decision Making (MADM) approaches, where some courses of action are chosen in the presence of multiple, usually conflicting, features. An interesting observation is that similar approaches have also been investigated in the Machine Learning community with the use of Probabilistic Graphical Models, such as Decision Networks or Influence Diagrams [37], but with the possibility of learning both the structural relationship among the attributes and their quantification in terms of uncertainty (probability) and utility. Finally, agent-based simulation is a completely different alternative, where no specific modeling is assumed, but the results are obtained by looking at the interactions among the involved agents. The crucial point is to determine the right set of simulation parameters, such as the number of agents, the rate of interaction, the probability of infection given by contacts, etc. In summary, all the approaches investigated in the different studies have their motivations, as well as their strengths and limitations, and no one can be, in general, considered better or worse than another one. However, the finding suggesting that quarantine is a good and efficient strategy for containing COVID-19 is an important result which is strengthened by the convergence of such different models.

Limitations of the study

Our study has limitations too. First, we did not have the possibility to use the risk of bias assessment tool, since no validated bias checklist is available. We draw conclusions from a few studies (n = 12). Additionally, some studies analyzed interventions in one single country. Therefore, we cannot conclude that they can also be efficient in other countries [21,23–27]. It was also difficult to distinguish the consequences of a single policy measure from those of other policy interventions. Although there were a variety of mathematical methods for unravelling relationships in structural components, none of them were ideal. However, it's important to note a potential limitation of these studies: they were conducted at the onset of the pandemic, prior to the emergence of COVID-19 variants. These new variants may exhibit different transmission patterns compared to the original strain, potentially impacting the effectiveness of intervention strategies analyzed in these studies. Additionally, the introduction of national vaccination programs could significantly alter the dynamics of the epidemic and the efficacy of various interventions over time. Therefore, while the findings from these studies provide valuable insights, caution should be exercised in directly applying them to current contexts influenced by new variants and vaccination efforts.

Conclusion

Despite the possible limitations, the outputs of AI and ML were generally consistent with the results obtained by most of the public health interventions that have been used to reduce the spread of COVID-19 worldwide. Our study findings showed that AI and ML could have been useful to help policy makers to better define the best strategies for containing the COVID-19 pandemic since the end of the first wave. As a matter of fact, at least half the articles (four of the seven for which dates could be clearly identified) were published in April 2021 or later—with the last two being "published" in May and June 2021, respectively. In particular, quarantine clearly emerged as the best strategy for containing COVID-19. On the contrary, a strict quarantine was rarely adopted worldwide. Additionally, according to AI and ML outputs, total, early and time extensive nationwide lockdown should have been adopted to stop the second wave because of the effectiveness in reducing the Rt and the transmission of the disease. On the contrary, such a measure was rarely adopted fully and often has been continuously mitigated according to the variations in the local risk of the spread of the disease. In fact, even though this strategy could not stop the pandemic, it was probably more acceptable because it did not drastically affect the people's degree of freedom due to the pandemic [39]. Social distancing should have been considered effective only with a combination of interventions, but again it was also widely adopted as a single intervention. We believe that this happened because most of the public interventions for preventing the second wave were implemented based mainly on them mechanistic or biological plausibility. On the contrary, they could have taken advantage of the use of AI and ML outputs. Even though the time lag between when the decisions needed to be made and these data appeared to be ready to be used makes our finding more effective as a summative evaluation than as a process evaluation, we suppose that, soon, Al and ML should play a significant role in public health policy making.

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