Review

The Application of Artificial Intelligence in Health Care Resource Allocation Before and During the COVID-19 Pandemic: Scoping Review

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Abstract

Background: Imbalanced health care resource distribution has been central to unequal health outcomes and political tension around the world. Artificial intelligence (AI) has emerged as a promising tool for facilitating resource distribution, especially during emergencies. However, no comprehensive review exists on the use and ethics of AI in health care resource distribution.

Objective: This study aims to conduct a scoping review of the application of AI in health care resource distribution, and explore the ethical and political issues in such situations.

Methods: A scoping review was conducted following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews). A comprehensive search of relevant literature was conducted in MEDLINE (Ovid), PubMed, Web of Science, and Embase from inception to February 2022. The review included qualitative and quantitative studies investigating the application of AI in health care resource allocation.

Results: The review involved 22 articles, including 9 on model development and 13 on theoretical discussions, qualitative studies, or review studies. Of the 9 on model development and validation, 5 were conducted in emerging economies, 3 in developed countries, and 1 in a global context. In terms of content, 4 focused on resource distribution at the health system level and 5 focused on resource allocation at the hospital level. Of the 13 qualitative studies, 8 were discussions on the COVID-19 pandemic and the rest were on hospital resources, outbreaks, screening, human resources, and digitalization.

Conclusions: This scoping review synthesized evidence on AI in health resource distribution, focusing on the COVID-19 pandemic. The results suggest that the application of AI has the potential to improve efficacy in resource distribution, especially during emergencies. Efficient data sharing and collecting structures are needed to make reliable and evidence-based decisions. Health inequality, distributive justice, and transparency must be considered when deploying AI models in real-world situations.

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KEYWORDS

artificial intelligence; resource distribution; health care; COVID-19; health equality; eHealth; digital health

Introduction

Global responses to COVID-19 are converging with the use of digital health and algorithms based on artificial intelligence (AI), impacting health care systems around the world [1]. AI was partially founded by Alan Turing, and a machine or a process that could demonstrate intelligent behaviors in cognitive tasks, which can pass the Turing test, would be deemed as AI [2]. Multiple AI techniques, such as fuzzy expert systems and Bayesian networks, have been applied both virtually and physically in the health care field [3]. For example, clinical pathway analysis, a critical area in ensuring standard medical procedures, can be analyzed by pattern-mining procedures [4]. Resource distribution includes the distribution of resources at strategic, tactical, and operational levels and is a key issue in health policy [5,6].

Luengo-Oroz et al proposed that the application of AI during the COVID-19 pandemic can be broken down into 3 scales: molecular, clinical, and societal [7]. At the molecular level, protein structure prediction, novel nucleic acid testing, drug repurposing, and drug discovery all rely on AI and deep-learning algorithms [7-9]. At the clinical level, diagnosis, treatment, and prognosis all benefit from AI. For example, AI-based computed tomography diagnosis has been widely applied for identifying COVID cases [7,10,11], alongside robotics and telemedicine that facilitate clinical processes. At the societal level, AI is applied in epidemiological research and social policymaking. In particular, AI-based case forecasting has been in use since the beginning of the pandemic [7,12]. The application of AI at the societal level can stratify population risk, facilitate diagnosis and testing, support the design of trials and drugs, and inform policymaking, relieving the burden of COVID-19 on health care systems and helping the society to better respond to the pandemic [1].

The application of AI to decision-making processes in health care systems significantly precedes the COVID-19 pandemic [7,13]. Health policy aims at providing health care to the population, and the decision-making process aims to address 2 core issues: screening and diagnosis, and treatment and monitoring [7]. These 2 tasks are essential to the entire health care system. The policymaking process includes hypothesis generation, hypothesis testing, and action (or policy). AI can learn from past data, including health records, past insurance claims, and disease incidence and prevalence, to improve hypothesis generation and testing, and thus improve the quality of health care policymaking [7].

In the health care system, resource distribution is an essential issue for policymakers, as resources are always scarce [14]. For example, Kong et al argued that the primary problem in China's health care system is the lack of high-quality health resources and the consequent supply-demand imbalance. They maintain that AI could benefit from China's enormous data and has the potential to improve this unequal distribution of health resources [14].

During the COVID-19 pandemic, imbalanced health care resource distribution has been one of the central issues causing unequal health outcomes and political tension [15,16]. Ji et al observed that the higher COVID case-fatality rate in Wuhan city and Hubei province compared with other parts of China at the beginning of the pandemic could potentially be attributed to health care resource scarcity [16]. Edejer et al projected that the cost of health care resources to combat the pandemic would continue to rise in low- and middle-income counties, and concluded that a comprehensive system of resource distribution is necessary [15].

Health care resource distribution is determined by the supply-demand relationship, logistics, and governance structure [17,18]. Using the COVID-19 response as an example, the severity of the pandemic can determine the health care resources required in each location, but the resources might not be distributed according to need [18]. AI can be applied to study supply-demand, logistics, and patient characteristics, but the ethics and implications of the use of AI in policymaking remain important issues [7].

Currently, there are no comprehensive reviews to provide an overall picture of the literature on the application of AI in resource distribution in health care settings, particularly with regard to societal and ethical aspects. This study aims to conduct a scoping review on the application of AI in health care resource distribution, particularly during the COVID-19 pandemic and to explore the ethics and implications of AI in health policymaking with regard to resource distribution.

Methods

Scoping Review Design

This scoping review follows the framework proposed by Arksey and O'Malley [19]. Briefly, the review has the following 5 stages: (1) identifying the research question, "What are the roles of AI and machine learning in the allocation of health care resources, before and during the COVID-19 pandemic?"; (2) identifying suitable studies; (3) selecting studies for review; (4) consolidating the data; and (5) summarizing and reporting the results. This study complies with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) [20] for reporting scoping review results.

Data Source and Search Strategy

Searches were conducted in MEDLINE (Ovid), PubMed, Web of Science, and Embase from inception to February 2022. The search featured 2 key terms: (1) *artificial intelligence*, including related terms such as *big data* and *algorithm*, and (2) *health care resource allocation*. The search terms were used with the "explode" feature where applicable. For example, in MEDLINE and Embase, we used *exp artificial intelligence/* and *exp resource allocation/*, and in PubMed, relevant MeSH (Medical Subject Heading) terms were used. The search was individually designed and adapted for each database.

Study Selection

Inclusion and exclusion criteria were defined a priori. This scoping review includes qualitative and quantitative studies investigating the application of AI in health care resource allocation. Studies that are not relevant to AI or health care resource allocation were excluded, as were duplicate studies. The inclusion and exclusion criteria are summarized in Table 1.

Selection was conducted in 2 steps. First, titles and abstracts were screened for topic relevance and study design. Second, full texts of the remaining studies were screened to check for eligibility. All of the study selection processes were conducted in EndNote X9 (Clarivate).

Table 1. Inclusion and exclusion criteria.

Criterion	Inclusion	Exclusion
Type of study	Qualitative, quantitative, mixed method, and review studies in peer-reviewed journals	Letters, comments, conference abstracts, editorials, and theses
Language	English	All other languages
Study variables	Includes (1) artificial intelligence/machine learning and relevant terms and (2) allocation of health care resources	Does not include (1) artificial intelligence/machine learning and relevant terms or (2) allocation of health care resources
Study context	Health care resource allocation at either the population level or hospital level	All other resource allocation scenarios

Data Consolidation

Selected studies were input into NVivo 12 (QSR International) for labeling and coding. Authors coded data of interest from the articles in NVivo 12 and extracted information regarding study author, study design, location, context, aim, main result, AI method under study, resource allocation situation, and policymaking relevance into a standardized Excel (Microsoft Corp) form.

Summarizing the Results

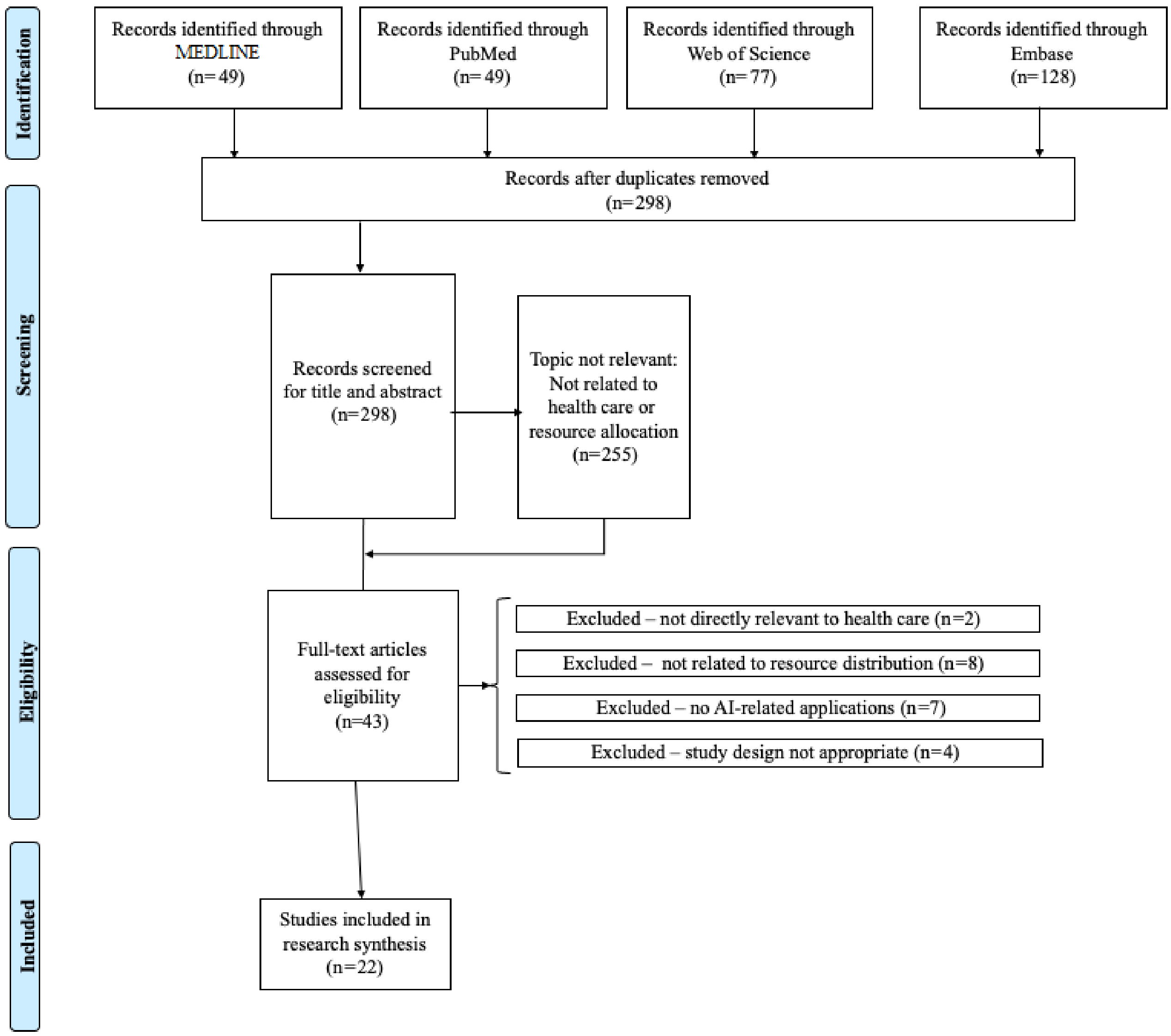
We employed an inductive approach to summarize the results from the included studies. First, the selected papers were grouped into 2 types: (1) studies of model development and validation of AI-based algorithms applied to health care resource distribution, and (2) qualitative studies, theoretical discussions, and review studies of the application of AI in health care resource distribution. For studies of model development and validation, we extracted the study objectives, resource distribution situations, AI model input variables, and policy relevance. For studies in the second category, objectives, resource distribution situations, discussed topics, and policy relevance were extracted. We further divided the input variables of the studies of model development and validation into 2 predefined categories: (1) ecological variables or variables at the group level, which included variables depicting characteristics at the population level, such as infant mortality in a region, local economic development, or disease prevalence and incidence; and (2) individual variables, which included variables that define individual characteristics such as diagnosis and age.

Results

Selected Studies

In total, 298 studies were identified in 4 databases after removing duplicates. After 1 round of screening for titles and abstracts, 255 studies were excluded due to irrelevant topics and unsuitable study designs. This left 43 studies for full-text screening. Of these, 2 were excluded because they were not directly relevant to health care, 8 because they were not related to resource distribution, 7 because they did not feature applications of AI, and 4 because of an inappropriate study design. In the end, 22 studies remained for qualitative synthesis. The PRISMA flow diagram for study selection is presented in Figure 1.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of the study. AI: artificial intelligence.



Summary of the Characteristics of Studies on Model Development

The characteristics of the included studies on model development are summarized in Table 2. The included studies were published between 2013 and 2021. Of the 22 included studies, 9 focused on model development and validation [21-30]. Of these, 5 studies were conducted in emerging economies, including 2 in China [27,29], 2 in Brazil [25,28], and 1 in Ecuador [26]. In developed countries, 3 studies were conducted. These included 1 in Germany [23], 1 in the United Kingdom [22], and 1 in the United States with a validation data set in China [24]. One study was applied to a global context [21].

Of the 9 studies, 4 focused on resource distribution at the health system level, including financial resources for public health in Brazil [25], health care resource distribution in health planning in Ecuador [26], medical resource allocation in the hierarchical health system in China [29], and medical equipment allocation in the global COVID-19 pandemic [21]. The remaining 5 studies focused on resource allocation at the hospital level, including bed allocation in a London hospital [22], day resources and bed allocation in a hospital in Munich, Germany [23], human resources and medical materials in a public hospital in China [27], medical resource allocation in a hospital in the capital of State of Minas Gerais in Brazil [28], and medical resource allocation in clinics for COVID-19 patients in New York [24].

Table 2. Characteristics of the included studies on model development and validation.

Reference	Objectives	Resource allocation situation	Input variables
Rosas et al (2013) [25]	To construct a financial resource allocation model using an artificial neural network	Financial resources for public health in Brazil	Mortality characteristics, proportion of teenage mothers, proportion of inadequate prenatal care, fertility rate, Gini index, proportion of elderly people in the population, literacy rate, financing capacity per capita, percentage of people with income below half minimum wage, percentage of urban households with basic sanitation, and proportion of urban households served by garbage collection
Belciug & Gorunescu (2015) [22]	To propose a bed allocation and financial resource utilization strategy through queuing modeling and evolutionary computation	Bed allocation and financial resource utilization in the geriatric department of a London hospital	Bed inventory, arrival rate, mean service time, patient flow parameters, and holding and penalty cost and other cost considerations
Gartner & Padman (2015) [23]	To evaluate how early determination of diagnosis-related groups can be used for better allocation of scarce hospital resources	Hospital resources, including day resources and overnight resources (beds), validated in a mid-sized hospital near Munich, Germany	Primary and secondary diagnoses, clinical procedures, age, gender, and weight in newborns
Velez et al (2016) [26]	To present an artificial intelligence–based health planning model based on data from geospatial systems	Health care resource distribution in health planning in Ecuador	Geospatial variables based on the social determinants of health and geospatial patterns of territorial distribution in the allocation of equipment, supplies, and health services in relation to the availability, accessibility, and need of the population
Xu et al (2018) [27]	To propose a health resource allocation model based on mass customization to maximize revenue and customization	Allocation of doctors and other medical resources in a public hospital system in China	Distribution of medical stations, professional level of doctors (salary and seniority), patient preferences and illness severity, medical cost, and revenue
Yousefi et al (2018) [28]	To present a model based on agent-based simulation, machine learning, and a genetic algorithm for allocation of medical resources in emergency departments	Medical resource allocation in a teaching hospital in the capital of State of Minas Gerais in Brazil	Number of receptionists in the reception area; number of triage nurses in the triage room; number of laboratory technicians in the laboratory and X-ray room; and number of doctors, nurses, and nurse technicians in the suturing yellow zone, orthopedics department, surgical department, and clinical emergency area.
Zhang et al (2018) [29]	To propose a framework introducing a novel approach to multi-attribute decision-making problems in the picture fuzzy context	Medical resource allocation in the hierarchical medical treatment system in China	Patient diagnostic characteristics and hospital tiers
McRae et al (2020) [24]	To present a clinical decision-support system and mobile app to assist in COVID severity assessment, management, and care	Resource allocation during COVID in New York, with validation data sets from Wuhan, China	Outpatient score (age, gender, diabetes, cardiovascular comorbidities, and systolic blood pressure) and biomarker score (C-reactive protein, procalcitonin, and age)
Bednarski et al (2021) [21]	To study how reinforcement learning and deep-learning models can facilitate the redistribution of medical equipment during pandemics	Pandemics in the context of COVID	COVID risk factors by region, COVID mortality by region, and current demand for medical equipment

Summary of the Characteristics of Studies Involving Reviews and Theoretical Discussions

The characteristics of studies involving reviews and theoretical discussions are summarized in Table 3. Of the 22 included studies, 13 were theoretical discussions, qualitative studies, or review studies [31-43]. Of those studies, 8 studies were qualitative discussions on the COVID-19 pandemic [31,33,34,36,38,39,41,43], with 2 in a Chinese context [34,43] and the rest in a global situation. The remaining 5 studies focused on other situations, with 1 focusing on resource allocation in intensive care units and hospital stay [40], 1 on disease outbreaks and disasters [33], 1 on diabetic retinopathy screening [42], 1 on human resource allocation in health systems [35], and 1 on medical information digitalization [37].

Table 3. Characteristics of the included studies involving theoretical discussions, qualitative studies, or review studies.

Reference	Objective	Resource allocation situation	Reviewed/discussed methods for the application of AI[a] during the COVID-19 pandemic
Rajkomar et al (2018) [40]	To explore how model design, biases in data, and interactions of model predictions with clinicians and patients exacerbate health inequalities	Intensive care unit and in-hospital stay length	• Suggested that future AI models for health care resource distribution should include principles of distributive justice.
Laudanski et al (2020) [36]	To analyze the applications of AI during COVID using the WHO[b] framework of pandemic evolution	Global COVID-19 pandemic	• Reviewed cases in Italy where AI was used in studying computed tomography scans for COVID prognosis, and suggested that AI-driven scans can help predict prognosis and therefore allow better resource distribution. • Discussed AI-driven triage based on patient characteristics and AI-supported health resource allocation and ethics.
Adly et al (2020) [31]	To discuss the potential of using AI to prevent and control COVID	Global COVID-19 pandemic	• Suggested that the application of AI was valuable in medical resource distribution that included the parameters of patients and the pandemic.
Bernardo et al (2020) [33]	To present approaches for using technology to facilitate resource distribution in disasters and outbreaks	Disasters and disease outbreaks	• Found that data collected from crowdsourcing and the human-technology interface could be used as data sources.
Neves et al (2020) [38]	To discuss the basic principles of medical resource allocation choices during COVID	Global COVID-19 pandemic	• Discussed rationalization of care, medical and team conflict, modeling of the pandemic, and application of AI. • Explored the use of AI as a support tool to streamline inventory control and standardize resource distribution.
Xie et al (2020) [42]	To present an overview of the application of AI technology in ophthalmology, with a focus on deep-learning systems	Diabetic retinopathy screening	• Reviewed empirical considerations behind the formation of successful screening programs. • Examined potential methods for health economics and safety analyses that can assess concerns regarding AI-based screening.
Zou et al (2020) [43]	To present the COVID response of Shenzhen, China and discuss the potential of a successful model for COVID prevention and control	COVID-19 pandemic in Shenzhen, China	• Reviewed methods applied by Shenzhen, including early action and centralized response, care for vulnerable persons, community response teams, and technology. • Discussed the integration of information technology in Shenzhen's response, including mobile technology, big data, and AI.
Basit et al (2021) [32]	To discuss the data sharing and collection process and the ethical considerations around pandemic data	Global COVID-19 pandemic	• Discussed the required data, failures and challenges in obtaining pandemic data, success in data access, model creation using data, and ethical challenges associated with data access during the COVID-19 pandemic. • Discussed the application of AI in the allocation of intensive care resources and ventilators.
Huang et al (2021) [34]	To investigate China's health informatization, especially during the COVID-19 pandemic	COVID-19 pandemic in China	• Discussed the development of China's health informatization from 5 perspectives: health information infrastructure, information technology applications, financial and intellectual investment, health resource allocation, and the standard system.
Jain et al (2021) [35]	To discuss the implications of AI for employability by analyzing issues in the health care sector	Human resources in health systems	• Displayed hierarchical relationships between employability and a range of characteristics. • Discussed measures that could potentially enhance employability in the health care sector through AI.
Lu et al (2021) [37]	To establish barriers that affect medical information digitalization innovation and development through interviews and a literature review	Medical information digitalization	• Applied the importance-resistance analysis model and identified the resistant factors, including data sharing, infrastructure, regulation, and operations in the context of data privacy. • Proposed several ways to overcome these limitations, including transparency regulation and infrastructure building.

Reference	Objective	Resource allocation situation	Reviewed/discussed methods for the application of AI[a] during the COVID-19 pandemic
Pereira et al (2021) [39]	To present interindividual variability and the roles it plays in the variability of COVID presentation and susceptibility.	Global COVID-19 pandemic	• Reviewed the biological differences that contribute to variability in COVID manifestation. • Reviewed efforts to use AI to integrate digital data to enable the identification of high-risk COVID-19 patients.
Röösli et al (2021) [41]	To discuss possible bias in the application of AI during the COVID-19 pandemic	Global COVID-19 pandemic	• Discussed how COVID exacerbated racial and socioeconomic disparities. • Explored how an AI-informed resource allocation strategy can be influenced by biases.

[a]AI: artificial intelligence.

[b]WHO: World Health Organization.

Summary of the Policy Implications of the Selected Studies

The policy implications of studies on model development are relevant on 2 levels: (1) health system level [21,25,26,29] and (2) hospital level [22-24,27,28], corresponding to situations where the models were applied. Detailed policy implications of the included studies on model development are summarized in Table 4. The qualitative and review studies focused largely on 2 issues: (1) how AI can promote the efficacy of resource allocation [21,32,34-37,39,42,43] and (2) the ethics and equality issues associated with using AI systems [38,40,41]. One study highlighted the lack of AI studies on resource distribution during COVID-19 [31]. Table 5 summarizes the policy implications of these studies.

Table 4. Policy relevance of the included studies on model development and validation.

Reference	Policy relevance
Rosas et al (2013) [25]	• Divided municipalities in Brazil into quartiles of health care financial needs. • Proposed that the selection of input variables should consider the vulnerability of the population, the true representation of the factors of need, political choice, and the availability of reliable data.
Belciug & Gorunescu (2015) [22]	• Provided tools to estimate the appropriate parameters for optimal resource utilization. • Enabled the hospital manager to simulate scenarios to make the near-best decision.
Gartner & Padman (2015) [23]	• Provided decision-makers with information on admission and scheduling decisions. • Offered an approach to integrate and analyze the financial objectives of health care delivery.
Velez et al (2016) [26]	• Facilitated the management of multidisciplinary information with the entire range of determinants of a specific context. • Provided enough flexibility to allow the exploration of different complex circumstances in health planning.
Xu et al (2018) [27]	• Reduced costs by making doctors mobile. • Addressed personal preferences, such as treatment time and the professional level of doctors.
Yousefi et al (2018) [28]	• Decreased the average length of stay in this emergency department case study by 14%. • Provided a framework to efficiently combine simulation and metamodels in the health care industry.
Zhang et al (2018) [29]	• Facilitated decision-making to divide patients under different conditions into different levels of hospitals in the hierarchical medical treatment system.
McRae et al (2020) [24]	• Supported the validity of a clinical decision support system and mobile app • Provided tools to be deployed to community clinics and sites for decision support.
Bednarski et al (2021) [21]	• Facilitated officials managing future public health crises. • Improved algorithm performance for future applications.

Table 5. Policy relevance of the included studies involving theoretical discussions, qualitative studies, or review studies.

Reference	Policy relevance
Rajkomar et al (2018) [40]	• Proposed that the principles of distributive justice be incorporated into model design, deployment, and evaluation.
Laudanski et al (2020) [36]	• Suggested that AI[a] can couple outbreak data with measures of potential demand and direct supplies more efficiently.
Adly et al (2020) [31]	• Found that no study had been published on the application of AI in medical resource distribution during the COVID-19 pandemic as of 2020 and that such studies are required to inform policy decisions.
Bernardo et al (2020) [33]	• Suggested that automation by AI and machine learning can further our abilities in predictive analytics.
Neves et al (2020) [38]	• Emphasized that the ethical values for the rationing of health resources in an epidemic should converge with basic ethical values and that transparency is essential to ensure public trust.
Xie et al (2020) [42]	• Proposed that technical feasibility and patient acceptability must be assessed for AI to be deployed in real-world settings, and that health professionals' acceptance and interpretability of AI-based screening strategies must also be assessed.
Zou et al (2020) [43]	• Proposed that the model adopted in Shenzhen, including multisectoral coordination, proactive contact tracing and testing, timely isolation and treatment, hospital infection control, effective community management, and prompt information dissemination, could be a potential model for other cities around the world for containing the pandemic.
Basit et al (2021) [32]	• Proposed that informaticians globally should continue collecting, recording, and analyzing data with the intent of gathering new knowledge and translating it into a better, faster, and more successful response to the next pandemic. • Suggested that professionals must come together to develop ways to collect, standardize, and disseminate the data needed to make necessary decisions.
Huang et al (2021) [34]	• Suggested that China's health informatization needs to strengthen top-level design, increase investment and training, upgrade health infrastructure and information technology applications, and improve internet-based health care services.
Jain et al (2021) [35]	• Proposed that an AI intervention could impact the employability of the workforce through operational and training changes, and therefore impact human resource distribution in health.
Lu et al (2021) [37]	• Provided a basis for the future development directions of medical information digitalization and its impacts on health care and health systems.
Pereira et al (2021) [39]	• Suggested that predicting which COVID-19 patients will develop progressive diseases that require hospitalization has important implications for clinical trials targeting outpatients.
Röösli et al (2021) [41]	• Proposed that transparency in reporting of AI algorithms is necessary to understand intended predictions, target populations, hidden biases, and class imbalance problems.

[a]AI: artificial intelligence.

Case Study Comparison: China and Brazil

China and Brazil are both developing countries with a similar per capita gross domestic product (China: US $10,435 and Brazil: US $6797) [44]. During the COVID-19 pandemic, Brazil has had one of the highest national overall cases and mortalities, as well as per capita cases and mortalities, with 29.5 million cases and 656,000 deaths as of March 2022 [45]. China has had one of the lowest per capita infection rates in the world, with a total of 124,000 cases and 4636 deaths as of March 2022 [45]. Given the similarity between the 2 countries in economic development and the enormous difference in COVID cases and mortalities, the resource distribution situation in the 2 countries is worth exploring.

Rosas et al [25] proposed a financial resource allocation algorithm for the public hospital system in Brazil based on mortality, socioeconomic characteristics, and income inequality. They argued that the choice of input variables for health care policymaking should consider the vulnerability of the population to being manipulated by those who manage public policy, the true representation of the factors of need, exemption from the process of political choice, and the availability of reliable data. The focus of the model was regional economic characteristics.

Zhang et al [29] proposed a model for the allocation of medical resources and tier classification of patients in China's health system, with the input variables of patient characteristics and hospital tiers, and a focus on differentiation into different tiers based on patients' disease severity. Xu et al [27] proposed a health resource allocation model for the allocation of doctors and other medical resources in a public hospital system in China that considered the distribution of medical stations, the professional level of doctors (salary and seniority), patient preferences and illness severity, medical cost, and revenue.

Overall, the allocation of medical resources based on the models from the 3 studies demonstrated that the key considerations proposed by studies from China were the hospital tier system, the professional level of doctors, the geographical distribution of medical resources, and cost-effectiveness [27,29]. However, the model proposed for Brazil focused on the regional economic situation [25].

Discussion

Principal Findings

In this review, we compiled evidence on the application of AI in health resource distribution, especially regarding COVID-related policy. After synthesizing 22 articles, we found that AI-based models were proposed at both hospital (secondary care in inpatient settings) and health system (public health) levels and that theoretical discussions and reviews focused on the potential for AI to improve the efficacy of resource distribution and on the ethics of applying AI in health resource distribution. Two major themes emerged from the review. First, we found that AI-informed resource distribution strategies are impactful for health access and equality. Second, the approaches can be categorized ideologically into revisionist and conservative groups.

Impact of an AI-Informed Resource Distribution Strategy on Health Access and Equality

AI and machine learning have considerable potential to improve efficacy in resource distribution, especially during emergencies, such as the COVID-19 pandemic, where quick decisions are required based on evolving situations [34,39,43]. For example, health informatization, particularly digital contact tracing and AI-informed response design, played an instrumental role in responding to COVID in China and helped local governments to improve efficacy in allocating limited resources [34,43]. AI can also be used to interpret diagnostic results and patient characteristics in order to predict disease progression and allocation of medicines, hospital beds, and medical professionals at the hospital level [21,39].

However, very large amounts of data are necessary for AI algorithms to make reliable and evidence-based decisions [46]. Health care institutions globally must therefore collect, record, and analyze data. This will help policymakers gather novel insights and translate the data into a prompt, equal, coordinated, and more successful response to the next pandemic [32,47]. As such, data collection must be institutionalized. The disparity in data collection capacity potentially exacerbates the gap in decision-making quality between countries [48,49]. For example, from the literature, China's information infrastructure and data-sharing agreements expedited the data-gathering process, a possible consequence of the centralized government system that facilitated gathering data, which in turn made the data set larger and more comprehensive [48]. In contrast, a selected study showed that Brazil's decentralized government system, with heterogeneous policies on data privacy and data sharing, made the collection and consolidation of data difficult [49]. However, caution should be taken in interpreting those results, as there is no evidence that the studies selected here are representative of the real situation in China or Brazil.

The included articles highlighted the importance of distributive justice and transparency in AI model design. The analysis conducted by Rajkomar et al emphasized that machine learning systems should be used proactively to advance health equality [40]. They proposed that distributive justice should be a core principle in AI models, including during the design, deployment, and evaluation processes. This perspective would include equality in patient outcomes, performance for every sociodemographic group, and resource allocation for each group. As Neves et al noted, resource allocation by AI and in emergencies should build on basic ethical values, including the equal value of people, instrumental value, and priority for critical situations. Transparency is the key to gaining trust when distributing resources [38].

Revisionist and Conservative Approaches in AI-Derived Resource Distribution

The build-up of AI models and implementation plans can be broadly categorized into revisionist and conservative approaches. In revisionist approaches, the models aim to revise the disparity in resource distribution by actively correcting the biases in previous decision-making processes. For example, the models proposed by Rosas et al [25] for financial resource allocation in Brazil emphasized consideration of income inequality, vulnerable populations, political choices, and the availability of reliable data. In conservative approaches, the models rely on traditional metrics, including supply and demand, profitability, and, perhaps most notably, previous decisions. This was demonstrated in a proposed model for the allocation of medical resources and tier classification of patients in China's health system by Zhang et al [29], where the input variables were patients' characteristics and hospital tiers, and a model suggested by Xu et al [27] for the allocation of doctors and other medical resources in a public hospital system in China, where the input variables included the distribution of medical stations, the professional level of doctors, patient preferences and illness severity, medical cost, and revenue. Doctor expertise, patient characteristics, hospital tier, and location are common variables in human decision-making, but AI has the potential to analyze the data more thoroughly.

However, despite the revisionist model proposed by Brazilian academics [25], health inequality is a prevailing issue in Brazil across states and social classes, both before [50] and during the COVID-19 pandemic [51]. Health inequality in Brazil increased across states from 1990 to 2016 [43]. Comparatively, the health care access and quality index in China was higher than that in Brazil in 2016, suggesting better equality and health care access in China [52]. However, due to the limitation of the research method, this study could not show the policymaking processes in both countries. From the selected studies alone, we observed that although proposing revisionist AI models to address health inequality should be encouraged, the application and practicality of using those models to inform health policy decisions and improve inequality should also be important considerations for researchers.

Strengths and Limitations

This is one of the first reviews to incorporate all available evidence qualitatively and provide a comprehensive picture of the model development and theoretical discussion on AI in medical resource distribution. Our results contribute to the ongoing discussion of applying AI in medical resource distribution and add novel insights into the social and ethical implications. Nonetheless, this study has several limitations. First, due to the scope of the study, we focused on published journal articles but did not examine policy documents or grey literature. This could have led to incompleteness in the collected information. Further studies could examine policy statements and grey literature to better understand intercountry differences. Second, we included only articles published in English and therefore might have overlooked publications in other languages. Third, there are potential sources of meaningful heterogeneity in this scoping review, including the diverse use of AI technologies, different study designs, and different locations. The analyses in this study could be affected by such heterogeneities. Fourth, this study is a qualitative overview of the general application of AI in health care resource distribution and is exploratory. We did not compare different levels of resource distribution and distinguish various machine learning methods in detail. Further studies are needed to explore and contrast different AI approaches at various resource distribution levels in detail. Lastly, due to the availability of evidence, we only compared studies from China and Brazil. We were only able to compare the differences between the 2 countries based on a few studies, which could not represent the real situation in either country. The comparison should be interpreted as exploratory and demonstrative.

Conclusions

This scoping review synthesized evidence on the application of AI in health resource distribution, particularly during the COVID pandemic. The included studies suggested that AI and machine learning have high potentials to improve efficacy in resource distribution, especially during sudden and evolving situations. A coordinated and continuous data sharing and collecting mechanism is needed for better data input so that AI can make reliable and evidence-based decisions. Various issues, including health inequality, distributive justice, and transparency, should be considered when deploying AI models. Such considerations are required for implementing revisionist AI models that can correct distribution inequality in actual policy processes.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence

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