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Data Quality, Bias, and Strategic Challenges in Reinforcement Learning for Healthcare: A Survey

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ABSTRACT

Data quality is a critical aspect of data analytics since it directly influences the accuracy and effectiveness of insights and predictions generated from data. Artificial Intelligence (AI) schemes have grown in the existing era of technological advancement, which provides innovative exposure to healthcare applications. Reinforcement Learning (RL) is a subfield and an influential Machine Learning (ML) model aimed at optimizing decision-making by association with dynamic environments. In healthcare applications, RL can modify conduct strategies, enhance source application, and improve patient investigation history by using various data modalities. The worth of the data quality regulates how effective RL is in healthcare applications. In healthcare, the model predictions have a direct impact on patient's lives, and poor data quality often leads to wrong evaluations that expose patient safety and treatment quality. Biases in data quality have also presented a challenging influence on the RL model's effectiveness and accuracy. RL models have enormous potential in healthcare; however, various strategic limitations prevent their widespread acceptance and deployment. The implementation of RL in healthcare faces serious issues, mostly around data quality, bias, and tactical difficulties. This study delivers a broad survey of these challenges, emphasizing how imbalanced, imperfect, and biased data can affect the generalizability and performance of RL models. We critically assessed the sources of data bias, comprising demographic imbalances and irregularities in electronic health records (EHRs), and their impact on RL algorithms. This survey aims to present a detailed study of the complex circumstances relating to data quality, data biases, and strategic barriers in RL models deploying in healthcare applications. However, the main contribution of the proposed study is that it provides a systematic review of these challenges and delivers a roadmap for future work intended to refine the consistency, fairness, and scalability of RL in healthcare sectors.

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1. INTRODUCTION

Recently, the integration of RL and the issues of the medical field offered advanced solutions to the healthcare domain [1]. RL model is widely used among different AI models due to its ability to use different AI approaches. RL has emerged as a strong pattern because of its capability in the decision-making process with dynamic settings [2]. RL has various hidden potentials in the healthcare area, such as enhanced medical significance, enriched source civilization, and reformed behaviour procedures [3]. Yet, for the RL to be smoothly incorporated into the intricate healthcare system, three difficulties must be resolved [4]: Signifying that the essential data is accurate, pointing to the slight causes of biases in healthcare datasets [5], and specifically unbearable challenges distinctive to the healthcare area. This survey aims to examine these vital structures in depth in instruction to afford bright trials related to using RL in healthcare and provide support for upcoming growth. RL depends on the data that initiates the learning manners of intelligent individuals [6]. The consistency and adeptness of RL processes in the medical field depend upon the quality of the data on which they are skilled [7]. In this survey, we deal with a complete study of data quality, observing the different causes, techniques, and methods of training that reinforce the datasets that constitute RL imitations for healthcare applications. The dynamic nature of healthcare data makes distinct challenges that require real-time decision-making, a complete consideration of interpretability, and the maintenance of rigorous values of data veracity [8]. Clear and hidden bias in healthcare datasets is a tenacious concern that can have a significant impact on the impartiality and generalizability of RL simulations [9] [10]. This survey aims to detect schemes that help in the growth of reasonable and justify RL models' application in medicinal surroundings. Besides, moral worries about the maintenance of bias and its latent penalties are inspected, adopting a broad understanding of the ethical ramifications of RL in the healthcare sector [11]. Currently, RL has revealed great potential in healthcare applications and is mostly focused on medical decision-making [12]. Difficulties that involve cautious routing include patient privacy, harmony, moral problems, and the difficult nature of real-world beneficial circumstances [13]. This survey stares at these planned trials and pulls assumptions from recently applied outlines and principles to put a bright eye on the trail to the ethically and correctly complete mixing of RL into healthcare actions. By presenting an extensive study, we are confident we can deliver academics, consultants, and legislators with a thorough indulgence of the serious features related to the claim of RL in healthcare. We pursue to offer a roadmap for achieving the full possibility of RL while steering the trials of the healthcare area by carefully studying data value, assessing partiality, and examining planned difficulties. The final unbiased is to aid in outlining an upcoming in which RL increases medical decision-making while remaining steadfastly correct to moral, reasonable, and data-integrity values for remedial claims.

The influence of this study on the field is its in-depth examination of the critical challenges surrounding data quality, bias, and strategic issues in employing RL in healthcare. It delivers a strong understanding of how these issues impact the performance of RL models in healthcare applications, deals with a categorized review of existing approaches for addressing these hurdles, and defines strategic recommendations to overcome them. This work progresses the domain by suggesting solutions that boost RL methods' consistency, fairness, and applicability in healthcare, finally contributing to further efficient and reasonable healthcare results.

The dominance of this work over others in the literature lies in its wide-ranging technique to identify the different challenges of data quality, bias, and tactical issues in RL within healthcare settings. Current works emphasize these aspects to present a general overview of the obstacles in the field.

This study not only concentrates on review but also on actionable strategic recommendations that directly mark these issues. By classifying existing approaches, examining their merits and demerits, and proposing new schemes to decrease these difficulties. This work delivers unique visions that cover beyond traditional literature evaluations. This method assists in bridging gaps in the current research, making RL applications more trustworthy and unbiased from healthcare perspectives. The main contribution of this study is given below:

- This proposed study carefully examines the serious challenges associated with data quality. These issues often lead to report performance in RL models, affecting their outcomes and reliability in healthcare applications.
- The study thoroughly reviews existing techniques to handle RL's data quality and bias issues. It classifies these techniques into clear classes, describing their usefulness in real-world healthcare applications and tackling their limitations.
- Based on the examination, the proposed study suggests actionable policies to decrease the identified data quality and bias obstacles. These recommendations aim to refine the consistency and impartiality of RL models in healthcare, adopting developments that support more precise and reasonable decision-making in healthcare settings

The remaining paper is structured as follows: Section 2 describes the background especially the paper focused on data quality, biases, and barriers in the RL of the healthcare sector. Section 3 shows the proposed methodology. Section 4 presents the results and discussion. Section 5 describes the conclusion of this study and makes suggestions for future work.

2. LITERATURE REVIEW

This section provides an overview of the work on data quality, bias, and strategic barriers of RL in healthcare applications with the pros and cons of these studies:

Previous studies have carefully examined these issues in RL for the healthcare sector, but they normally focus on a single aspect of these issues. There is a lack of detailed studies that identify these issues simultaneously, considering their interdependencies and combined impact on RL performance in healthcare applications. This survey paper is fascinating since it takes a multidisciplinary method to observe the challenges in RL for the healthcare sector. This study presents an inclusive outline for attempting worries associated with data quality, bias, and strategic impairments, as compared to earlier research that emphasizes individual issues. This comprehensive lookout is vital for creating durable RL systems that can be steadily and ethically employed in medical surroundings, finally leading to more rational and effective patient care solutions. This discovers the serious challenges associated with data quality, bias issues, and strategic obstacles, emphasizing the most relevant studies in the desired domain. RL is inimitable among AI approaches since it can learn the best course of action by interrelating with its environments. The growing potential of AI, mainly RL, to develop healthcare applications.

The pros of assimilating RL into healthcare involved its capability to process huge quantities of data, providing a level of accuracy and personalization that far exceeds human competencies. This permits faster detection of cure selections, enhanced decision-making, and the progress of personalized treatment strategies. Moreover, RL systems can acquire and adjust over time, leading to more refined and correct forecasts of medical consequences and, finally, improving patient care. Yet, there are remarkable cons. RL models rely deeply on the obtainability of high-quality data, and errors or biases in the data can be central to imprecise inferences, possibly putting patients at risk. Furthermore, the difficulty of RL models can make them tough to understand, making challenges in achieving belief from healthcare specialists. Besides, assimilating RL into current healthcare schemes needs important computational resources, knowledge, and expertise, which can be an obstacle to extensive adoption [14].

There are numerous factors in the healthcare segment ranging from medicinal imaging to the investigation of disease. The earlier work debates the close association between radiomics, RL in Healthcare (RLHC), and medical decision support systems. RLHC and radiomics share a mutual goal of increasing adapted medication by employing massive healthcare data. Radiomics emphasizes mining high-throughput measurable features from medicinal images. RLHC applies this data to grow modified treatment strategies. The integration of these technologies generates a more precise and data-driven technique to enhance investigations and personalized treatments.

The pros of this incorporation were important, such as radiomics increasing analytical and prognostic correctness by examining image-based features in cancer investigation. Mutual with RLHC, this permits more modified and accurate forecasts of nearly persistent results. RLHC influences the visions from radio mic data to advance individualized behaviour and treatment strategies. Furthermore, the data-driven technique delivered using technologies makes medical choices more impartial, which could potentially lead to enhanced patient maintenance across different healthcare spheres. With appropriate standardization and procedures, radiomics and RLHC could be extensively employed to renovate healthcare performance.

Conversely, there are prominent cons that want to be addressed. One of the key challenges is the deficiency of standardization in radio mics in the achievement and assessment of image data. This discrepancy can interrupt the assimilation of radio mics into medical training consequences. The difficulty of both RLHC and radio mics also offers authentication challenges, as their procedures need severe testing to certify correctness. The adoption of these technologies may face confrontation without standardized evaluation criteria. Another con is the belief in high-quality data, which can be challenging to gain due to differences in imaging approaches and inadequate datasets. Besides, the application of these systems demands considerable computational resources and association between medical physicists and clinicians, generating practical challenges for routine medicinal implementation [15].

Different phases employed in medical management fluctuate from the emergency maintenance unit to treatment at home. This study delivers visions of serious hospital-level maintenance to older patients at home, highlighting its feasibility and effectiveness in the U.S. context. The data demonstrate that this approach led to appropriate care that encountered worth values and was related to rarer problems. For instance, disorientation and the use of sedative medicines are different from old-style hospital maintenance. The study's key advantage is its delivery of exhaustive medicinal management, containing regular doctor visits and one-on-one nursing caution, which is unusual in earlier hospital-at-home models. It presented decreased prices and higher patient and family gratification. On the other hand, the study had some cons. Patients were not arbitrarily allocated, presenting a potential collection of bias. Incomplete data from some contributors more restricted the outcomes. The consequences were also not generalizable to other diseases or health schemes as the study concentrated on a select group of identified and detailed health strategies. The involvement at one study site presented lower membership, possibly due to Indigenous healthcare issues such as nursing deficiencies [16].

Each feature of the healthcare region and every phase of scientific conduct has its significance. RL provides smart solutions to making well-organized strategies in different healthcare areas, where the decision-making procedure is typically considered by a lengthy historical or consecutive process. Exploring the potential of RL in enlightening decision-making processes across different healthcare claims, with HIV therapy, sepsis management, and epilepsy conduct. RL's main benefit is its aptitude to optimize orders of decisions to attain long-term consequences, contrasting traditional AI methods that emphasize one-time forecasts. In sepsis management, for instance, RL supports clinicians in determining when to recruit and regulate cures like antibiotics or mechanical freshening by examining patient data (lab tests, vital signs) and creating activities that can increase both short-term and long-term health effects.

The connotation between these studies lies in their common objective of employing RL to optimize healthcare choices. Each study highlights the use of RL in varied medical backgrounds, from handling complex treatments to refining patient conditions. RL suggests clear cons, such as allowing more adapted policies in healthcare decisions. One important pro is that RL delivers an outline for learning from past data and enhancing treatment plans over time. Major rewards and long-term objectives are puzzling, as seen in sepsis management, where perfect cure targets remain uncertain. The cons of RL systems are that they require high-quality data and clinician input for prize strategy, which can obscure the enactment process. Misappropriation of RL could repeat bad performance if processes are not correctly certified, underlining the necessity for carefulness in smearing these schemes in healthcare [17].

However, there are numerous problems with employing RL in the healthcare system because of difficulties with data quality, biases that are current, and strategic barriers. For RL to be effectively applied in healthcare applications, these issues must be determined. This survey aims to comprehensively inspect these issues, emphasizing the current position of the area and directing out knowledge gaps that are essentially identified to effectively increase RL in healthcare. Data quality is an essential requirement for any ML application, including RL. In the healthcare system, the data utilized for training RL algorithms normally come from electronic health records (EHRs) sensor data and medical imaging. The RL is employed to identify the trials of handling intricate illnesses like diabetes and sepsis by optimizing cure plans. The link between this study and other RL-based healthcare investigations is beached in their communal aim of educating modified drugs by leveraging data-driven methods. Both studies employ RL to advance consecutive decision-making in medicinal surroundings. The pros of the study comprise the capacity to model self-motivated, heterogeneous data and elevate treatments, which can lead to better patient consequences, such as better-quality glucose regulators for patients. However, there are cons, like the convolution of the RL systems and the requisite for high-quality EHR data. The interpretability of the models is an experiment that is addressed by seeing key physical variables, but there are leftovers to the issue of simplifying these approaches across diverse patient inhabitants. The computational properties necessary for such methods may confine their general execution in clinical sceneries [18].

Different studies emphasize how serious it is to handle these strategic roadblocks to warrant that RL is effectively applied in healthcare. The operating healthcare data captures important features for cultivating healthcare facilities while adjusting budgets. It supports other exploration that influences ML and RL for advanced health policies, such as it also discovering the character of progressive systems in processing healthcare data. The association between this study and other RL-based healthcare research lies in their public accent on using data-driven methods to recover and enhance quantifiable consequences. Whereas RL is employed for uninterrupted decision-making in action, ML procedures in healthcare analytics emphasize classifying patterns and fashions from huge datasets, which can later notify choices or treatment attitudes.

The pros of their work its courtesy of feature selection and the use of ML techniques to grip the complications of healthcare information. Which can meaningfully progress healthcare competence by providing more correct guesses. The capability to examine information from numerous healthcare foundations as pharmaceutical companies hospitals, and insurance agencies makes this method effective and appropriate across diverse healthcare subdivisions.

Still, the cons consist of the contests of allocating mixed and high-dimensional information, which confuses the feature collection procedure. Moreover, the study highlights the requirement for more well-organized data recovery approaches to fully influence ML procedures. While they suggest answers for these contests, implementation in real-world settings may face practical problems, such as data quality and the required integration of ML models and computational resources into current healthcare schemes[19]. Table 1 describes the relevant work in which, if the study reported a definite factor regarding data quality biases and hurdles, it is denoted by (✓). If not reported, then by (✗).

Table 1. Summary of Literature on Data Quality, Bias Concerns, and Strategic Obstacles in RL for Healthcare Applications

Study	Data Quality	Bias Issues	Obstacles	Challenges	Proposed Solutions	Generalizability	Broad Method	Key Findings	Strengths	Limitations
[20]	✓	✗	✗	✗	Data cleaning, EHR focus	Moderate	✗	Emphasized issues of inconsistent healthcare data in RL.	A wide-ranging study of EHR data issues.	Emphases mainly on EHR data, not further bases
[21]	✓	✗	✗	✗	Progressive preprocessing	Moderate	✗	Report diverse data and planned preprocessing methods	Domain-specific complaint approaches	Partial to precise preprocessing methods
[22]	✓	✗	✓	✓	DRL-LVT structure for video source provision in D2D nets	Moderate	✓	Important enhancements in proficiency, consistency, and flexibility in real-time distant patient observing	Smart, adaptive, and real-time decision-making procedures	Deficiencies explicit reference to speaking bias concerns
[23]	✗	✓	✓	✗	Suggests that choosing effective proxies for ground truth can reduce bias	Low	✗	Address important racial bias in an extensively used healthcare system, in which Black patients are noticeably sicker than White patients at the same risk score.	Reports the matter of healthcare charges as a proxy for disease, which familiarizes racial bias	Concentrated on a single system and its bias may not report all features of bias in other processes.
[24]	✓	✗	✓	✓	DRL systems personalized to precise IoT use, a broad study of benefits and issues	Broad	✓	Extensive review of DRL Techniques in IoT applications, notification of crucial matters to report	Inclusive study of DRL methods and their extensions in IoT usage	Issues in policies, rewards, and current DRL techniques in IoT use.
[25]	✗	✓	✗	✗	Impartiality restraints	Moderate	✗	Suggested fairness restraints and combative debiasing methods.	Advanced bias alleviation methods.	It may not simplify across all healthcare settings
[26]	✓	✗	✗	✗	Collaborating usage by clinicians, irrespective of original analytics	Moderate	✗	Emphasis on collaborative decision support systems for multifarious	Promises significant assistance in interpreting large and	Limited to the methods and quality of underlyin

								medical conditions	complex data sets	g analytic methodol ogies
[27]	✓	✓	✓	✓	Enhanced precision, efficiency, and workflow	Moderate	✓	AI influences at three stages: clinicians (appearance clarification), health schemes (workflow, fault discount), patients (self-data treating)	Employs improved calculating influence and cloud storing; latent for important enhanceme nts in medicinal performs	Existing confines contain bias, secrecy/sa fety concerns, and a dearth of clarity.
Prop osed	✓	✓	✓	✓	Combined structure	High	✓	Recognized the interplay between data quality, bias, and strategic hindrances.	Offers a combined structure for RL issues.	Limited by the depth of assimilati on of answers.

3. METHODOLOGY

The proposed methodology provides comprehensive and well-structured research, making it possible to fully understand the advantages and drawbacks of relating RL to healthcare applications. The survey objectives are to inform legislators, experts, and the academic community regarding the different dimensions of RL operation in the healthcare domain by following systematic stages. The use of RL in the healthcare area has been a cumulative consideration in recent years [28], as demonstrated by extensive research from numerous sources in academia. This is proved by a considerable frame of investigation from an extensive choice of academic bases. The inclusive analysis of the literature has been prepared viable by orderly record examines, notably PubMed [29], IEEE Xplore [30], and Google Scholar, as well as a cautious inspection of well-thought-of papers and symposium proceedings. Gandhi and Mishra [31] revolutionary learning discovers the use of RL in healthcare policymaking and climaxes the prospect for customized action tactics [32]. Their outcomes climax how RL algorithms can meaningfully advance persistent results, prominent the way for extra investigation in the ground of the healthcare system. Rahman and Al-Obeidat [33] employed provisional reproductive adversarial networks (C-GAN) to discover the association between five large behaviour traits and phishing-producing information preferences. Their investigation focused on the psychological elements that could influence an individual's susceptibility to phishing attempts and security in general. Kerr and Norris [34] carried out a thorough examination of RL techniques used in healthcare settings. Their analysis highlights the significance of comprehending the data quality that supports these models in addition to listing several RL models. The authors draw attention to how dynamic healthcare data is and how strong pretreatment methods are essential for decision-making, guaranteeing the accuracy of RL strategies. When tackling biases in medical data, seminal research by Norori and Hu [35] thoroughly assesses the demographic [36] and clinical biases [37] that are prevalent in commonly used healthcare datasets. Their research clarifies the difficulties posed by skewed data and suggests algorithmic fixes to reduce biases in DL and RL models. The work of Sun Sun [38] explores the strategic problems associated with using RL in healthcare settings. Their examination of privacy, permission, and data security issues in relation to ethics offers important new perspectives on the strategic challenges associated with RL integration. They also explore the intricacies of actual clinical situations, emphasizing the real-world obstacles that must be overcome for deployment to be successful. They offer a contextual framework for comprehending the situation of RL in health care. The studies that have been identified emphasize the significance of tackling issues related to data quality, biases [39], and strategic obstacles [40]. This will help to direct the further stages of our study.

Table 2. Research Utilizing RL in the Medical Field

Study	Year	Key Points
Yu, Liu [4]	2021	Summary of the main techniques and theoretical underpinnings of RL.
Ganju, Atasoy [41]	2020	Decision support systems' contribution to reducing racial bias in the delivery of healthcare

Abdellatif, Mhaisen [42]	2021	An Extensive Survey of RL for Intelligent Healthcare Systems
Mahmud, Kaiser [28]	2018	A detailed overview of the application of DL, RL, and deep RL algorithms in extracting biological information
Mulani, Heda [43]	2020	Personalized medical guidance based on deep RL
Javaid, Haleem [44]	2022	Machine learning's importance in healthcare: Features, foundations, and applications
Liu, Logan [45]	2017	Using medical registry data, deep RL for dynamic treatment regimens
Levine, Kumar [46]	2020	Emphasis on offline RL: Overview, analysis, and viewpoints on unsolved issues.
Kavitha, Roobini [47]	2023	A methodical examination of the principles, difficulties, and applications of AI in smart healthcare systems.

We hope that this study will add to the current study about RL and healthcare by highlighting important trends and approaches and pointing out any gaps that need more research. For several healthcare problems involving noisy data, RL offers a technically and statistically valid alternative to optimum decision-making. Table 2 represents a review of the RL approach used in healthcare.

3.1. Data Quality Analysis

Before diving into the details of data quality that support RL models in the context of healthcare applications, we conduct a thorough study of frequently used healthcare datasets in the context of RL research. This initial stage is critical to comprehending the environment in which RL models are constructed. This assign the datasets normally cited in the relevent study in health care domain that is baseline for this survey [48].
We identify the background reason for healthcare dataset creation employed in the RL application as well as conduct a detailed evaluation of the relevant dataset collection techniques. This entails an entire examination of the sources applied to collect healthcare data, many file formats utilized to record it, and the method of preparation to enhance the data's efficiency. With the deep evaluation of these details, the proposed study learned to concisely describe the nuances of processing data through RL policies, which perform an important understanding of the initial stages of the RL strategies [49]. The systematic detection of hurdles concerning high data quality in the range of healthcare sector is addressed. Different problems are involved, such as the versatile nature of patient history and investigation, changing policies of medical treatment and the needs and criteria of real-time updation [50]. Addressing these problems plays an important role in identifying how reliable and concise RL techniques are employed in the healthcare system. The identified problems influence essential aspects of the healthcare domain via RL.

The proposed study is summarized on the basis of three main steps: Dataset compilation, an overview of data collection techniques, and a systematic evaluation of different barriers that occurred in the assurance of the finest data quality [51]. Studies conducted on data quality examination in the healthcare system are shown in Table 3. Various factors could be the reason for addressing different trends and the sources of bias. They evaluated the demographic [36] and clinical biases that occurred in healthcare datasets [52].

3.2. Strategic Hurdles Exploration in RL

RL has great potential to improve resource allocation, individualized therapies, and decision-making in the healthcare industry [53]. This shift is not without difficulties, though. Examining the strategic barriers that prevent RL from being seamlessly integrated into healthcare procedures in detail uncovers a variety of intricate issues that need to be carefully taken into account [54]. Figure 1 shows the overview of the proposed study. A lot of the time, healthcare data is error-prone, complex, and heterogeneous [55]. One of the biggest challenges in RL training is ensuring the integrity and quality of the data. Strong procedures for data anonymization and protection are also required because of privacy issues brought up by the sensitive nature of healthcare information. Models with poor data quality may be prejudiced, and patient confidentiality may be jeopardized by insufficient privacy protections [56]. To ensure safety and effectiveness, RL models must be rigorously validated before being incorporated into clinical workflows [57]. Complying with regulatory standards [58], such as those set by health authorities, increases the complexity and duration of procedures. Table 4 represents different types of bias assessment raised in healthcare datasets, while Table 5 represents strategic challenges and their implications.

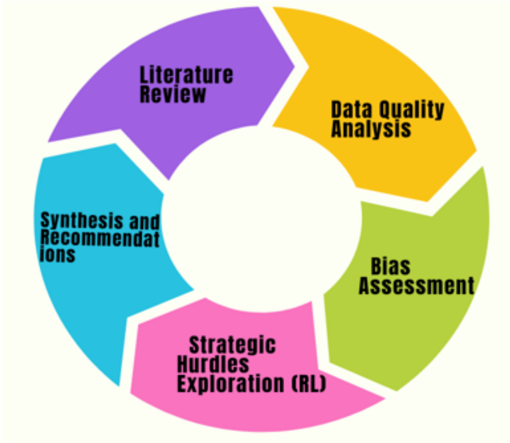

Figure 1. Overview of the Proposed Work

Table 3. Studies which Show Data Quality Analysis

Study	Year	Key Points
[59]	2022	Scoping analysis and enhancement recommendations of R packages for quality evaluations and data monitoring.
[60]	2021	Assessment of data quality to choose datasets for offline RL
[61]	2024	An analysis looking into the relationship between the quality of patient clinical data and the interface characteristics of electronic health records.
[62]	2017	Beyond data cleansing and transformations, data quality considerations for big data and machine learning
[63]	2019	Veracity in patient-reported results: variables influencing patients' reactions and their influence on the calibre of the data
[64]	2019	Finding systematic problems with the quality of data in electronic health records
[65]	2018	Examining data quality aspects in the context of big data in the health sector: Data governance.
[66]	2023	Enhancing Data Quality: Approaches, Difficulties, and Effect on the process of decision.
[67]	2023	Assessment of Data Quality for Digital Decision Support in the Estonian National Health Information System
[68]	2023	The healthcare industry's massive data management issue and the use of cloud computing techniques

Table 4. Bias Assessment for Healthcare Using RL Models

Dataset	Study	Biases
Electronic Health Records (EHR)	[69]	Biases in information and selection
Clinical datasets	[70]	Healthcare disparities based on demographics
Electronic health record (EHR) data	[71]	Informed Presence Bias Illustration
Sub-physionet datasets	[72]	Unreported bias in heart sound datasets from PhysioNet
UCI Heart Illness Dataset	[73]	Prediction With Limited Features, missing values
AI Data Sets	[74]	The sparsity of dataset descriptions, the lack of transparency, inconsistent disease labelling, and the absence of reporting regarding patient variety.
SEER Dataset	[75]	Inherent biases
Medical data	[76]	Cognitive biases
Oncology Data Sets	[77]	Bias and Unequal Classification in Cancer Data
SKCM dataset	[78]	Sampling bias, class labelling bias, class correlated bias
Skin lesion datasets	[79]	(De)Assembling Bias: Positive and Negative Bias
Breast Cancer Surveillance Consortium (BCSC) dataset.	[80]	The biases associated with errors in radiologists' assessments of mammograms and their effects on clinical decision-making.

Table 5. Strategic Hurdles Exploration

Study	Challenge	Implications
[81]	Data standardization	Interoperability can be hampered by a lack of standards, making it difficult to integrate and share data between various systems.
	Managerial skills	The quality and usability of data may be hampered by unstructured or improperly managed data due to ineffective data governance.
	Security	Insufficient security protocols may result in the breach of confidential patient data, undermining confidence and possibly breaking privacy laws.
	Data structure disputes	Interoperability can be hampered by a lack of standards, making it difficult to integrate and share data between various systems.
	Storage and Transfers	Ineffective methods for data transit and storage might cause delays, data loss, or higher operating expenses.
[82]	Creating the Reward Mechanism	A reward function could result in recommendations that are not ideal and affect the overall efficacy of the RL algorithm.
	Assessing the condition of the patient using electronic	Patient states from electronic health records could impair the quality of suggestions generated by the RL model.
[83]	Crisis in Human Resources	Hampered access to healthcare, which reduced the efficacy of relief efforts nationally.
	Insufficient Resources in Difficult Environments	Influencing the impacted population's health results
	Insufficient Funding for Humanitarian Medical Care	A lack of funding could make it more difficult to deploy enough healthcare professionals.
	Factors Restricting the Availability of Human Resources	Impacting the range and standard of medical care provided during emergencies.
	Insufficient Instructional Guidelines	This can lead to a lack of confidence in the qualifications of people recruited for particular positions, which could jeopardize the standard of healthcare service.
	Absence of Task-Based Capabilities	It can decrease the possible pool of workers and may hamper the optimal exploitation of human resources in humanitarian efforts.
[84]	Bias and Unfairness of Algorithm Themes	It can lead to undesirable results.
	Brittleness and generalizability of the algorithm	could weaken the algorithm's resilience in a variety of conditions, affecting its overall efficacy and dependability
[85]	complex data of the healthcare system	Often leads to ill-understood
	Ground-truth label generation can be costly or unfeasible.	This may restrict the supply of reliable training data, impeding the creation and functionality of ML models.
	Standardization and privacy concerns restrict data sharing.	This can hinder teamwork and the development of large-scale datasets, which could hinder the progress that ML research may make.
	Discrimination and laws pertaining to the "right to an explanation."	This can lead to presents moral and legal dilemmas
[86]	Algorithmic Bias	can make it difficult to recognize and deal with biases
	Transparency and interpretability issues with AI models	It may be difficult to recognize and correct biases in AI models if they are opaque and difficult to interpret.
	Dataset Bias	Inequitable Algorithmic Results

[87]	Data privacy, security, and quality; technical constraints and biases in the data	This can result in issues with reliable, equitable, and efficient models.
	Scarcity of data scientists	Restricting Insights and Innovation
	Recruits, including the panic of new technologies	Opposition to Emerging Technologies
[88]	Restricted access to high-quality training data	Diminished Effectiveness of the Model
	Unsafe exploration	This can lead to hazardous overexposure.
[89]	Tackling Ethical Obstacles	This can lead to bias risk and concerns over patients' moral relationship with the ML system.
[90]	Computational difficulty of a substantial amount of data	Can get expensive

3.3. Synthesis and Recommendations

The field of RL in the healthcare industry is active, with many potential problems to be faced. Understanding important discoveries and trends in a nuanced way shows how ethical issues, complex healthcare systems, and technology improvements interact in a complex way [91]. Sophisticated methods of data anonymization and safe frameworks for data sharing can alleviate privacy issues, and methodical ways of enhancing data quality are necessary for objective training of models [92]. Table 6 indicates the synthesis of different studies conducted in the healthcare system and their recommendation.

Table 6. Synthesis and Suggestions for RL in Healthcare

Study	Aspect	Key Findings	Key Trends
[93]	Privacy and Data Quality Issues	Challenge: It's critical to protect the privacy and quality of data.	Trend: Improvements in frameworks for safe sharing and data anonymization.
[94]	Explanation and Interpretation	Challenge: Insufficient interpretability limits trust.	Trend: Investigations on explainable RL and AI methods.
[95]	Clinical Verification and Adherence to Regulations	Challenge: Complying with strict validation requirements takes time.	Trend: Joint efforts to create precise rules and expedite validation procedures.
[96]	Big Data privacy and security concerns in the medical field	Challenge: Privacy of Patients, Data Security	Trend: Utilizing Blockchain Technology to improve medical data security and integrity
[97]	Biases in healthcare data	Challenge: Addressing Biases in medical data	Trend: Reducing bias in cardiac disease risk surveillance with electronic health records: separating the signal from the noise
[98]	An intelligent healthcare monitoring system to forecast heart problems	Challenge: Lack of a conceptual framework leading to high-dimensional datasets	Trend: A suggested smart healthcare system uses feature fusion and ensemble deep learning to forecast cardiac disease.
[99]	Medical Ontology in a Changing Healthcare Setting	Challenge: More costly, competitive, and complex due to the use of varied professions and embedded gadgets.	Trend: Constructing apps to deliver business services in a productive, varied, and extremely dynamic setting.
[100]	Dynamics of complexity: Managerialism and Unpleasant Emergence in healthcare institutions	Challenge: Difficulties with poisonous attitudes and workplaces	Trend: Alternative management strategies that can bring up adaptive change without incurring negative consequences on people and societies.

[101]	Numerous conceivable patients	Challenge: Difficult to handle the sharp rise in the population of elderly and chronically sick people	Trend: AI-Powered Precision Medicine and Multidisciplinary Cooperation
[102]	Ageing adults' dental health	Challenge: chronic and most oral infection burden in old age	Trend: To translate knowledge into action plans for the oral health of older adults.

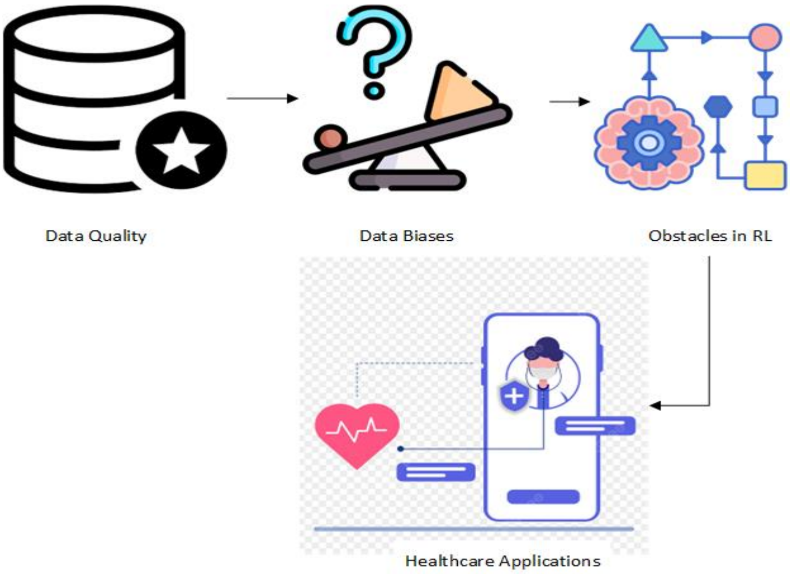

Figure 2. Steps Covered in the Proposed Study

3.4. Reinforcement Learning in Healthcare

RL in the healthcare domain has drawn an important consideration due to its latent to enhance management strategies, resource allocation, and decision-making processes. Its subfield of ML is where an agent studies to make decisions by interacting with an atmosphere. The agent attains response in the form of favourable or unfavourable significance based on its actions, and its objective is to learn a strategy that increases the cumulative incentive over time.

Here's a summary:

RL is applied to determine the most appropriate operative cure policies for individual patients based on their distinctive features and remedial history. The optimization technique has been employed to analyze diseases, such as brain tumour patients, to minimize patient treatment costs [103]. RL can help handle chronic infections such as cardiovascular diseases, diabetes, and asthma by constantly adjusting management strategies based on patient comments, physiological data, and lifestyle changes. An RL-based, modified preventative interference model to logically give oral medications to long-lasting patients over the progression of their lifetimes. The created model has states that include the patient's medication status and status for chronic difficulties, actions that include selecting the right drug and amending its dosage, and rewards that are contingent on the patient's post-medical treatment health [104]. Machine learning, such as RL, plays an important role in lesion categorization, lack of symmetry, and other suitable attributes in images attained from diverse modalities, like histopathological slides, X-rays, MRIs, and CT scans [105]. This expertise also extends to abnormality detection in which federated learning an RL keeps the ability to recognize specific patterns that could be signs of primary infection.

The proposed study steps are discussed in Figure 2. Personalized diagnosis and treatment planning are what differentiate RL; it may adjust suggestions based on patient profiles, medical histories, and past intervention reactions. This flexibility increases patient care through rapid analysis and treatment regimens, as well as streamlining the workflow of medical staff by mechanizing repetitive actions and providing decision support through prior knowledge guidance in image analysis, such as chest X-rays [106]. Finally, RL's tools for continuing learning and growth assure its applicability in a therapeutic field that is altering rapidly. This allows RL to stay existing with new developments while maintaining high values of accuracy and reliability. RL's role as a key module in refining medical imaging and analysis is more concreted by its potential for resource optimization, quality assurance, and fault reduction. This bodes well for an upcoming when healthcare involvements are more precise, effective, and modified [107]. Although there is potential for RL in the healthcare system, there are several obstacles that prevent RL from being extensively used and from working efficiently in this domain. Massive amounts of high-quality data are needed for training RL algorithms, but these might be difficult to come by in the healthcare system due to privacy issues, data bias, and data inconsistency formats and quality [108]. Missing values, label noise, and imbalances are common in medical data, which makes it challenging to train dependable deep learning and RL simulations [109]. Moreover, some more common issues include credit assignment, sample efficiency, investigation against maltreatment, and representation. The toxic triad unpredictability and/or difference caused by the combination of off-policy, function calculation, and bootstrapping is encountered by value function approaches with function approximation, particularly with (Deep Neural Network) DNNs. Deep RL has a reproducibility problem, meaning that many hyperparameters, such as recompense size and network design, random seeds trials, settings, and codebases, might distraught the results of trials [110]. Difficulties with reward terms can arise, and an incentive function might not precisely imitate the designer's goal. Issues like the expressivity of Markov reward [111] and delusional bias [112] are continuously being recognized and addressed by practitioners and researchers. Different hurdles that must be decreased earlier RL can be used in real-world circumstances. These problems consist of knowledge of a real system with small sample sizes, system interruptions, high-dimensional state and action spaces, meeting ecological restrictions, limited observability and non-stationarity, multi-objective or poorly specified reward functions, real-time inference, offline RL training from fixed logs, and reasonable and interpretable rules [113]. RL deployment lessons have been recognized by experts such as [114] and [115]. Keeping in mind that there are several problems, efforts are being made to solve them all, and reinforcement learning is a useful method for a variety of uses.

This study pointed out there are approaches that promise to solve all or even the mainstream issues, yet other approaches are enough to endeavour with a reasonable possibility of achievement for the popular optimization problem categories: distinct or nonstop, deterministic, stochastic, active, sports, etc. [116]. To overcome these obstacles, interdisciplinary cooperation between academics, clinicians, policymakers, and technological developers is required to generate ethically sound, understandable, and clinically established RL keys that address the occasions and difficulties faced by the healthcare system. Moreover, developing a culture of openness, responsibility, and ongoing development is essential to boosting confidence in RL-driven healthcare advances.

4. RESULTS AND DISCUSSION

In this paper, we studied different features of data quality, bias issues, and strategic hurdles in RL applications within the healthcare domain. The proposed study exposes that present RL techniques face remarkable problems due to data irregularities and partialities. This review in RL for healthcare applications reveals different critical insights and academic fields that require more concentration to assess this area efficiently. We detected that RL models accomplished on imbalanced datasets frequently exhibit reduced performance in understated demographic classes. There are some major limitations of previous studies, as discussed in this review, that need further evaluation. The one major limitation in RL healthcare application is reported in different prior works that have relied on biased, incomplete, inconsistent datasets. Reliable prediction created by RL measures runs the hazard of damaging patient conduct in the nonappearance of reliable, high-quality data. Another limitation reported in previous studies is the bias in the training data. Data collected from definite demographic groups may not signify wider residents, which is prominent in models that show performance ailing when applied to miscellaneous patient groups. Numerous RL models are enhanced based on historical medicinal data, which frequently transports intrinsic biases from past medical observations. This could preserve disparities in healthcare products rather than advance them, as RL schemes might strengthen biased medical decisions. Computational complications remain a serious limitation. RL processes usually need wide computational resources, which can confine their real-time applications in healthcare settings with limited resources. Several earlier works have not entirely addressed the issue of emerging further well-organized models that can control resource-constrained clinical atmospheres and time-sensitive emergency management. One disadvantage is the black-box nature of several RL models, which delays their interpretability.

Healthcare specialists want translucent models to faith AI-generated endorsements. Though numerous RL methods are impervious, they contribute a slight vision of how choices are prepared. This absence of explainability postures a main barricade to medical assumption, as it obfuscates belief, responsibility, and controlling authorization. Moreover, moral and legal challenges have been ineffectively discovered in earlier research. While RL systems hold the potential to refine patient results, the moral inferences of machine-driven healthcare decisions are multifaceted. Queries of accountability, particularly when RL models create mistakes, are left unreported. There is also worry concerning patient agreement and data confidentiality, as RL models need access to large quantities of complex health data. We assessed numerous current RL techniques in contradiction of a range of parameters such as fairness, accuracy, and generalizability. This survey specifies that progressive algorithms provide enriched constancy and competence compared to traditional tech iques. Conventional techniques still fight bias when trained on biased datasets. The consequences also highlight that assimilating progressive bias mitigation techniques can enhance model fairness. Our discussion highlights the critical necessity for improved data quality and bias alleviation policies in RL settings. Advanced RL techniques have made developments in controlling complicated healthcare data, but they remain vulnerable to biases characteristic of the training data. Addressing these problems needs a multidimensional technique comprising upgraded data collection approaches, consistent bias checks, and the incorporation of fairness-enhancing processes. RL, with developing technologies like federated learning, can deliver a favourable direction to overcome data quality issues and privacy. This study underlines the universal matter of data quality in the healthcare RL system.

Healthcare data, normally the result of EHRs, medical imaging, and sensor readings, is imperfect, boisterous, and heterogeneous. These inadequacies expressively influence the training and performance of RL models. Studies specify that while preprocessing methods, such as data cleaning and augmentation, can alleviate some data quality matters, they do not completely resolve the issue. Therefore, there is still a considerable need for further vigorous and universal methods to carefully grip the varied nature of healthcare data. Second, we have discussed the bias in healthcare data, which is another important trial recognized in this survey. Bias can arise from different sources, containing socioeconomic disparities, historical prejudices, and demographic imbalances in healthcare. The survey focused on RL models trained on biased data that can preserve and even worsen health inequalities, leading to unsatisfactory treatment consequences. Strategic hindrances contain the more general complications in employing RL in healthcare settings. Important difficulties discussed in the survey include moral concerns, model interpretability, controlling concerns, and assimilation with existing healthcare sectors. The assumption of RL is expressively hindered by the difficulty of the healthcare domain and the dynamic nature of regulatory rules. According to the poll, making robust moral standards and producing interpretable RL models are vital first steps in decreasing these issues. Moreover, generating a regulatory setting that supports invention while certifying patient safety and privacy is important for the efficacious placement of RL in the healthcare system. The survey exposes that though considerable research has been conducted on data quality, bias, and strategic obstacles separately, there is a lack of studies that note these challenges in an integrated mode.

This survey contributes to the current form of information by providing a manifold study of the challenges in smearing RL to healthcare. Unlike previous studies that emphasize individual issues, this work offers a combined context that reflects the interdependencies between data quality, bias, and strategic obstacles. By emphasizing these interrelated issues, the survey presents a more inclusive empathy of the barricades to operative RL applications in healthcare.

5. CONCLUSION AND FUTURE DIRECTIONS

This survey has provided a comprehensive examination of the critical issues affecting the utilization of RL in healthcare applications, concentrating on data quality, bias, and strategic obstacles. The findings highlight that although there have been noteworthy progressions in addressing separate aspects of these issues, an all-inclusive method that assimilates solutions across these areas is crucial for the fruitful application of RL in healthcare. Data quality issues, halting the integrally multifaceted and often defective nature of healthcare information, continue to delay the development of consistent RL systems. Concurrently, bias in data, arising from different systemic and historical aspects, is a danger to impartial healthcare consequences. This complete method is vital for overcoming the obstacles to implementation and exploiting the latent of RL in changing healthcare. The work on implementing RL in healthcare will go in new directions in the future, requiring a thorough and planned approach to solve present problems and open up fresh prospects. Enhancing model interpretability is essential, as it recognizes the need to go past RL models' "black box" status. The goal of increasing transparency should be the focus of researchers and developers so that medical practitioners can better comprehend and rely on their judgments. The development of strong ethical frameworks and rules is another essential path. Ethical considerations become critical machines using AI as RL models impact patient treatment more and more. Establishing precise guidelines guarantees the equitable, open, and responsible application of AI in healthcare environments. This is consistent with the overarching objective of integrating patient viewpoints into decision-making procedures via cooperative efforts involving patients, healthcare practitioners, and AI systems.

The creation of RL applications should be guided by human-centric design concepts to guarantee smooth integration into the current workflows in healthcare. Prioritizing usability and fit with the requirements of medical practitioners makes RL technology adoption more efficient and natural. Multidisciplinary collaboration is required from different fields, including data science, computer science, and medicine, for experts to augment the significance, moral insinuations, and, specifically, RL uses. Forming RL models that can increase medical decision-making in real-time is a fundamental region of highlighting. Real-time abilities are vital for RL applications since they can have a considerable influence on persistent consequences over timely interferences. For RL schemes to vigorously regulate time variations in patient well-being and alter healthcare performance, it is important to examine dynamic learning models. It is essential to report biases in RL facsimiles to enhance the quality of the health system. Research should look into how to diminish biases and assure impartial outcomes for a kind of demographic alliance. Identical validation is also essential to rationalize controlling defiance, making it calmer and organizing RL applications sensibly and efficiently. Endorsing intercontinental collaboration plans is essential to making illustrative and varied datasets for the RL model. These assurances that RL replicas are consistent and appropriate to a variety of healthcare surroundings and patient demographics. Another practical measure is to assimilate a detailed discussion into the exercise process that helps generate logically understandable models. After deployment, it is crucial to set up long-term monitoring and evaluation systems to evaluate continuing performance, spot changing biases, and guarantee continual progress. Maintaining RL models' long-term efficacy, safety, and fairness requires routine monitoring.

In the future, we aim to report different main zones to progress RL in healthcare. We will focus on exploring progressive bias alleviation methods, which will be central to making sure reasonable cure references are made for various patient cultural and demographic conditions. This can include purifying technique impartiality outlines to stability correctness with justice. Assimilating RL with advanced technologies such as federated learning, edge computing, and blockchain will improve scalability, data secrecy, and real-time decision-making. Considering real-world trials such as unfinished or raucous automated health records is also perilous. Increasing the number of vigorous models proficient in functioning under vagueness will develop the practical solicitation of RL in the healthcare domain. Moreover, future studies should emphasize creating interpretable RL models, permitting clinicians to better comprehend and have confidence in the treatment endorsements produced by these schemes. Longitudinal studies will be required to endorse the RL models' long-term effectiveness in the scientific and medical domains and improve patient conclusions over time. Lastly, the combination of multi-modal data comprising imaging data, hereditary data, and electronic healthcare data can enhance extrapolative healthcare applications and individualized cure tactics. The mentioned future directions deliver a roadmap to overcome present limitations and motivate invention in RL for healthcare. All of these future paths open the door to a more responsible, inclusive, and successful application of RL in medical procedures. Through the resolution of ethical issues, improvement of interpretability, promotion of teamwork, and awareness of the constantly changing healthcare environment, the profession can optimize advantages while minimizing hazards and difficulties.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest in this work.

REFERENCES

[1] A. Haleem, M. Javaid, and I. H. Khan, "Current status and applications of Artificial Intelligence (AI) in medical field: An overview," *Curr. Med. Res. Pract.*, vol. 9, no. 6, pp. 231–237, Nov. 2019, doi: 10.1016/j.cmrp.2019.11.005.

[2] A. Gosavi, "Reinforcement Learning: A Tutorial Survey and Recent Advances," *INFORMS J. Comput.*, vol. 21, no. 2, pp. 178–192, May 2009, doi: 10.1287/ijoc.1080.0305.

[3] Z. Ahmed, K. Mohamed, S. Zeeshan, and X. Dong, "Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine," *Database*, vol. 2020, Jan. 2020, doi: 10.1093/database/baaa010.

[4] C. Yu, J. Liu, S. Nemati, and G. Yin, "Reinforcement Learning in Healthcare: A Survey," *ACM Comput. Surv.*, vol. 55, no. 1, pp. 1–36, Jan. 2023, doi: 10.1145/3477600.

[5] B. Velichkovska, D. Denkovski, H. Gjoreski, M. Kalendar, and V. Osmani, "A Survey of Bias in Healthcare: Pitfalls of Using Biased Datasets and Applications," 2023, pp. 570–584. doi: 10.1007/978-3-031-35314-7_50.

[6] A. Fachantidis, M. Taylor, and I. Vlahavas, "Learning to Teach Reinforcement Learning Agents," *Mach. Learn. Knowl. Extr.*, vol. 1, no. 1, pp. 21–42, Dec. 2017, doi: 10.3390/make1010002.

[7] M. Siddiq, "Integration of Machine Learning in Clinical Decision Support Systems," *Eduvest - J. Univers. Stud.*, vol. 1, no. 12, pp. 1579–1591, Dec. 2021, doi: 10.59188/eduvest.v1i12.809.

[8] H. Javed, H. A. Muqeet, T. Javed, A. U. Rehman, and R. Sadiq, "Ethical Frameworks for Machine Learning in Sensitive Healthcare Applications," *IEEE Access*, vol. 12, pp. 16233–16254, 2024, doi: 10.1109/ACCESS.2023.3340884.

[9] B. Smith, A. Khojandi, and R. Vasudevan, "Bias in Reinforcement Learning: A Review in Healthcare Applications," *ACM Comput. Surv.*, vol. 56, no. 2, pp. 1–17, Feb. 2024, doi: 10.1145/3609502.

[10] J. Yang, A. A. S. Soltan, D. W. Eyre, and D. A. Clifton, "Algorithmic fairness and bias mitigation for clinical

machine learning with deep reinforcement learning," *Nat. Mach. Intell.*, vol. 5, no. 8, pp. 884–894, Jul. 2023, doi: 10.1038/s42256-023-00697-3.

[11] D. S. Char, M. D. Abràmoff, and C. Feudtner, "Identifying Ethical Considerations for Machine Learning Healthcare Applications," *Am. J. Bioeth.*, vol. 20, no. 11, pp. 7–17, Nov. 2020, doi: 10.1080/15265161.2020.1819469.

[12] S. Ellahham, N. Ellahham, and M. C. E. Simsekler, "Application of Artificial Intelligence in the Health Care Safety Context: Opportunities and Challenges," *Am. J. Med. Qual.*, vol. 35, no. 4, pp. 341–348, Jul. 2020, doi: 10.1177/1062860619878515.

[13] K. Naithani and S. Tiwari, "Deep Learning for the Intersection of Ethics and Privacy in Healthcare," 2023, pp. 154–191. doi: 10.4018/978-1-6684-8531-6.ch008.

[14] A. Coronato, M. Naeem, G. De Pietro, and G. Paragliola, "Reinforcement learning for intelligent healthcare applications: A survey," *Artif. Intell. Med.*, vol. 109, p. 101964, Sep. 2020, doi: 10.1016/j.artmed.2020.101964.

[15] P. Lambin *et al.*, "Radiomics: the bridge between medical imaging and personalized medicine," *Nat. Rev. Clin. Oncol.*, vol. 14, no. 12, pp. 749–762, Dec. 2017, doi: 10.1038/nrclinonc.2017.141.

[16] B. Leff, "Hospital at Home: Feasibility and Outcomes of a Program To Provide Hospital-Level Care at Home for Acutely Ill Older Patients," *Ann. Intern. Med.*, vol. 143, no. 11, p. 798, Dec. 2005, doi: 10.7326/0003-4819-143-11-200512060-00008.

[17] O. Gottesman *et al.*, "Guidelines for reinforcement learning in healthcare," *Nat. Med.*, vol. 25, no. 1, pp. 16–18, Jan. 2019, doi: 10.1038/s41591-018-0310-5.

[18] T. Li, Z. Wang, W. Lu, Q. Zhang, and D. Li, "Electronic health records based reinforcement learning for treatment optimizing," *Inf. Syst.*, vol. 104, p. 101878, Feb. 2022, doi: 10.1016/j.is.2021.101878.

[19] A. Veena and S. Gowrishankar, "Healthcare Analytics: Overcoming the Barriers to Health Information Using Machine Learning Algorithms," 2021, pp. 484–496. doi: 10.1007/978-3-030-51859-2_44.

[20] A. L. Beam and I. S. Kohane, "Big Data and Machine Learning in Health Care," *JAMA*, vol. 319, no. 13, p. 1317, Apr. 2018, doi: 10.1001/jama.2017.18391.

[21] A. E. W. Johnson *et al.*, "MIMIC-III, a freely accessible critical care database," *Sci. Data*, vol. 3, no. 1, p. 160035, May 2016, doi: 10.1038/sdata.2016.35.

[22] Z. Chkirbene, R. Hamila, D. Unal, M. Gabbouj, and M. Hamdi, "Enhancing Healthcare Systems With Deep Reinforcement Learning: Insights Into D2D Communications and Remote Monitoring," *IEEE Open J. Commun. Soc.*, vol. 5, pp. 3824–3838, 2024, doi: 10.1109/OJCOMS.2024.3412963.

[23] Z. Obermeyer, B. Powers, C. Vogeli, and S. Mullainathan, "Dissecting racial bias in an algorithm used to manage the health of populations," *Science (80-.).*, vol. 366, no. 6464, pp. 447–453, Oct. 2019, doi: 10.1126/science.aax2342.

[24] W. Chen, X. Qiu, T. Cai, H.-N. Dai, Z. Zheng, and Y. Zhang, "Deep Reinforcement Learning for Internet of Things: A Comprehensive Survey," *IEEE Commun. Surv. Tutorials*, vol. 23, no. 3, pp. 1659–1692, 2021, doi: 10.1109/COMST.2021.3073036.

[25] A. Rajkomar, M. Hardt, M. D. Howell, G. Corrado, and M. H. Chin, "Ensuring Fairness in Machine Learning to Advance Health Equity," *Ann. Intern. Med.*, vol. 169, no. 12, p. 866, Dec. 2018, doi: 10.7326/M18-1990.

[26] E. H. Shortliffe and M. J. Sepúlveda, "Clinical Decision Support in the Era of Artificial Intelligence," *JAMA*, vol. 320, no. 21, p. 2199, Dec. 2018, doi: 10.1001/jama.2018.17163.

[27] E. J. Topol, "High-performance medicine: the convergence of human and artificial intelligence," *Nat. Med.*, vol. 25, no. 1, pp. 44–56, Jan. 2019, doi: 10.1038/s41591-018-0300-7.

[28] M. Mahmud, M. S. Kaiser, A. Hussain, and S. Vassanelli, "Applications of Deep Learning and Reinforcement Learning to Biological Data," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 29, no. 6, pp. 2063–2079, Jun. 2018, doi: 10.1109/TNNLS.2018.2790388.

[29] R. K. Behera, P. K. Bala, and A. Dhir, "The emerging role of cognitive computing in healthcare: A systematic literature review," *Int. J. Med. Inform.*, vol. 129, pp. 154–166, Sep. 2019, doi: 10.1016/j.ijmedinf.2019.04.024.

[30] B. Singh, D. Lopez, and R. Ramadan, "Internet of things in Healthcare: a conventional literature review," *Health Technol. (Berl).*, vol. 13, no. 5, pp. 699–719, Sep. 2023, doi: 10.1007/s12553-023-00771-1.

[31] N. Gandhi, and S. Mishra, "Applications of Reinforcement learning for Medical Decision Making," *RTA-CSIT*, pp. 1–5, 2021.

[32] M. C. Liefaard *et al.*, "The Way of the Future: Personalizing Treatment Plans Through Technology," *Am. Soc. Clin. Oncol. Educ. B.*, no. 41, pp. 12–23, Jun. 2021, doi: 10.1200/EDBK_320593.

[33] A. U. Rahman, F. Al-Obeidat, A. Tubaishat, B. Shah, S. Anwar, and Z. Halim, "Discovering the Correlation Between Phishing Susceptibility Causing Data Biases and Big Five Personality Traits Using C-GAN," *IEEE Trans. Comput. Soc. Syst.*, vol. 11, no. 4, pp. 4800–4808, Aug. 2024, doi: 10.1109/TCSS.2022.3201153.

[34] K. Kerr, T. Norris, and R. Stockdale, "Data quality information and decision making: a healthcare case study," *ACIS 2007 Proc.*, pp. 1017–1026, 2007.

[35] N. Norori, Q. Hu, F. M. Aellen, F. D. Faraci, and A. Tzovara, "Addressing bias in big data and AI for health care: A call for open science," *Patterns*, vol. 2, no. 10, p. 100347, Oct. 2021, doi: 10.1016/j.patter.2021.100347.

[36] S. Abbasi-Sureshjani, R. Raumanns, B. E. J. Michels, G. Schouten, and V. Cheplygina, "Risk of Training Diagnostic Algorithms on Data with Demographic Bias," 2020, pp. 183–192. doi: 10.1007/978-3-030-61166-8_20.

[37] H. Zhang, A. X. Lu, M. Abdalla, M. McDermott, and M. Ghassemi, "Hurtful words," in *Proceedings of the ACM Conference on Health, Inference, and Learning*, New York, NY, USA: ACM, Apr. 2020, pp. 110–120. doi: 10.1145/3368555.3384448.

[38] X. Sun, Z. Sun, T. Wang, J. Feng, J. Wei, and G. Hu, "A Privacy-Preserving Reinforcement Learning Approach for Dynamic Treatment Regimes on Health Data," *Wirel. Commun. Mob. Comput.*, vol. 2021, no. 1, Jan. 2021, doi: 10.1155/2021/8952219.

[39] D. G. L. D.D. Terris, "Data quality bias: an underrecognized source of misclassification in pay-for-performance reporting?," *Qual. Manag. Healthc.*, vol. 17, no. 1, pp. 19–26, 2008.

[40] J. Zajas, "Obstacles to Real Strategic Marketing in Health Care," *J. Hosp. Mark.*, vol. 8, no. 2, pp. 19–31, Aug. 1994, doi: 10.1300/J043v08n02_04.

[41] K. K. Ganju, H. Atasoy, J. McCullough, and B. Greenwood, "The Role of Decision Support Systems in Attenuating Racial Biases in Healthcare Delivery," *Manage. Sci.*, vol. 66, no. 11, pp. 5171–5181, Nov. 2020, doi: 10.1287/mnsc.2020.3698.

[42] A. A. Abdellatif, N. Mhaisen, A. Mohamed, A. Erbad, and M. Guizani, "Reinforcement Learning for Intelligent Healthcare Systems: A Review of Challenges, Applications, and Open Research Issues," *IEEE Internet Things J.*, vol. 10, no. 24, pp. 21982–22007, Dec. 2023, doi: 10.1109/JIOT.2023.3288050.

[43] J. Mulani, S. Heda, K. Tumdi, J. Patel, H. Chhinkaniwala, and J. Patel, "Deep Reinforcement Learning Based Personalized Health Recommendations," 2020, pp. 231–255. doi: 10.1007/978-3-030-33966-1_12.

[44] M. Javaid, A. Haleem, R. Pratap Singh, R. Suman, and S. Rab, "Significance of machine learning in healthcare: Features, pillars and applications," *Int. J. Intell. Networks*, vol. 3, pp. 58–73, 2022, doi: 10.1016/j.ijin.2022.05.002.

[45] Y. Liu, B. Logan, N. Liu, Z. Xu, J. Tang, and Y. Wang, "Deep Reinforcement Learning for Dynamic Treatment Regimes on Medical Registry Data," in *2017 IEEE International Conference on Healthcare Informatics (ICHI)*, IEEE, Aug. 2017, pp. 380–385. doi: 10.1109/ICHI.2017.45.

[46] S. Levine, A. Kumar, G. Tucker, and J. Fu, "Offline reinforcement learning: Tutorial, review, and perspectives on open problems," *arXiv*, pp. 1–43, 2020.

[47] T. A. Shaikh, S. Hakak, T. Rasool, and M. Wasid, *Machine Learning and Artificial Intelligence in Healthcare Systems*. Boca Raton: CRC Press, 2022. doi: 10.1201/9781003265436.

[48] S. Mistry, L. Wang, Y. Islam, and F. A. J. Osei, "A Comprehensive Study on Healthcare Datasets Using AI Techniques," *Electronics*, vol. 11, no. 19, p. 3146, Sep. 2022, doi: 10.3390/electronics11193146.

[49] R. Lenz and M. Reichert, "IT support for healthcare processes – premises, challenges, perspectives," *Data Knowl. Eng.*, vol. 61, no. 1, pp. 39–58, Apr. 2007, doi: 10.1016/j.datak.2006.04.007.

[50] P.-T. Chen, C.-L. Lin, and W.-N. Wu, "Big data management in healthcare: Adoption challenges and implications," *Int. J. Inf. Manage.*, vol. 53, p. 102078, Aug. 2020, doi: 10.1016/j.ijinfomgt.2020.102078.

[51] S. E. Madnick, R. Y. Wang, Y. W. Lee, and H. Zhu, "Overview and Framework for Data and Information Quality Research," *J. Data Inf. Qual.*, vol. 1, no. 1, pp. 1–22, Jun. 2009, doi: 10.1145/1515693.1516680.

[52] D. P. Gopal, U. Chetty, P. O'Donnell, C. Gajria, and J. Blackadder-Weinstein, "Implicit bias in healthcare: clinical practice, research and decision making," *Futur. Healthc. J.*, vol. 8, no. 1, pp. 40–48, Mar. 2021, doi: 10.7861/fhj.2020-0233.

[53] R. M. Kaplan and D. L. Frosch, "Decision Making in Medicine and Health Care," *Annu. Rev. Clin. Psychol.*, vol. 1, no. 1, pp. 525–556, Apr. 2005, doi: 10.1146/annurev.clinpsy.1.102803.144118.

[54] M. M. Assadullah, "Barriers to Artificial Intelligence Adoption in Healthcare Management: A Systematic Review," *SSRN Electron. J.*, 2019, doi: 10.2139/ssrn.3530598.

[55] D. Pal, T. Chen, S. Zhong, and P. Khethavath, "Designing an Algorithm to Preserve Privacy for Medical Record Linkage With Error-Prone Data," *JMIR Med. Informatics*, vol. 2, no. 1, p. e2, Jan. 2014, doi: 10.2196/medinform.3090.

[56] S. Swain, B. Bhushan, G. Dhiman, and W. Viriyasitavat, "Appositeness of Optimized and Reliable Machine Learning for Healthcare: A Survey," *Arch. Comput. Methods Eng.*, vol. 29, no. 6, pp. 3981–4003, Oct. 2022, doi: 10.1007/s11831-022-09733-8.

[57] Y. Jia, T. Lawton, J. Burden, J. McDermid, and I. Habli, "Safety-driven design of machine learning for sepsis treatment," *J. Biomed. Inform.*, vol. 117, p. 103762, May 2021, doi: 10.1016/j.jbi.2021.103762.

[58] E. G. G. Verdaasdonk, L. P. S. Stassen, P. P. Widhiasmara, and J. Dankelman, "Requirements for the design and implementation of checklists for surgical processes," *Surg. Endosc.*, vol. 23, no. 4, pp. 715–726, Apr. 2009, doi: 10.1007/s00464-008-0044-4.

[59] J. Mariño, E. Kasbohm, S. Struckmann, L. A. Kapsner, and C. O. Schmidt, "R Packages for Data Quality Assessments and Data Monitoring: A Software Scoping Review with Recommendations for Future Developments," *Appl. Sci.*, vol. 12, no. 9, p. 4238, Apr. 2022, doi: 10.3390/app12094238.

[60] P. Swazinna, S. Udluft, and T. Runkler, "Measuring Data Quality for Dataset Selection in Offline Reinforcement Learning," in *2021 IEEE Symposium Series on Computational Intelligence (SSCI)*, IEEE, Dec. 2021, pp. 1–8. doi: 10.1109/SSCI50451.2021.9660006.

[61] O. O. Madandola *et al.*, "The relationship between electronic health records user interface features and data quality of patient clinical information: an integrative review," *J. Am. Med. Informatics Assoc.*, vol. 31, no. 1, pp. 240–255, Dec. 2023, doi: 10.1093/jamia/ocad188.

[62] V. Gudivada, A. Apon, and J. Ding, "Data quality considerations for big data and machine learning: Going beyond data cleaning and transformations," *Int. J. Adv. Softw.*, vol. 10, no. 1, pp. 1–20, 2017.

[63] E. M. Chang, E. F. Gillespie, and N. Shaverdian, "Truthfulness in patient-reported outcomes: factors affecting patients' responses and impact on data quality," *Patient Relat. Outcome Meas.*, vol. Volume 10, pp. 171–186, Jun. 2019, doi: 10.2147/PROM.S178344.

[64] C. N. Ta, and C. Weng, "Detecting systemic data quality issues in electronic health records," *Stud. Health Technol. Inform.*, vol. 264, pp. 383–387, 2019.

[65] S. Juddoo, C. George, P. Duquenoy, and D. Windridge, "Data Governance in the Health Industry: Investigating Data Quality Dimensions within a Big Data Context," *Appl. Syst. Innov.*, vol. 1, no. 4, p. 43, Nov. 2018, doi: 10.3390/asi1040043.

[66] R. Pansara, "Cultivating Data Quality to Strategies, Challenges, and Impact on Decision-Making," *Int. J. Manag. Educ. Sustain. Dev.*, vol. 6, no. 6, pp. 24–33, 2023.

[67] M. Bertl, K. J. I. Kankainen, G. Piho, D. Draheim, and P. Ross, "Evaluation of Data Quality in the Estonia National Health Information System for Digital Decision Support," *HEDA*, pp. 1–13, 2023.

[68] D. Kumar Sharma, D. Sreenivasa Chakravarthi, A. Ara Shaikh, A. Al Ayub Ahmed, S. Jaiswal, and M. Naved, "The aspect of vast data management problem in healthcare sector and implementation of cloud computing technique," *Mater. Today Proc.*, vol. 80, pp. 3805–3810, 2023, doi: 10.1016/j.matpr.2021.07.388.

[69] J. L. Vassy *et al.*, "Yield and bias in defining a cohort study baseline from electronic health record data," *J. Biomed. Inform.*, vol. 78, pp. 54–59, Feb. 2018, doi: 10.1016/j.jbi.2017.12.017.

[70] G. Kleinberg, M. J. Diaz, S. Batchu, and B. Lucke-Wold, "Racial underrepresentation in dermatological datasets leads to biased machine learning models and inequitable healthcare," *J. biomed Res.*, vol. 3, no. 1, p. 42, 2022.

[71] M. Phelan, N. A. Bhavsar, and B. A. Goldstein, "Illustrating Informed Presence Bias in Electronic Health Records Data: How Patient Interactions with a Health System Can Impact Inference.," *EGEMS (Washington, DC)*, vol. 5, no. 1, p. 22, Dec. 2017, doi: 10.5334/egems.243.

[72] M. Phelan, N. A. Bhavsar, and B. A. Goldstein, "Exploring Composite Dataset Biases for Heart Sound Classification," *AICS*, pp. 1–13, 2020.

[73] K. Mohammad Alfadli and A. Omran Almagrabi, "Feature-Limited Prediction on the UCI Heart Disease Dataset," *Comput. Mater. Contin.*, vol. 74, no. 3, pp. 5871–5883, 2023, doi: 10.32604/cmc.2023.033603.

[74] R. Daneshjou, M. P. Smith, M. D. Sun, V. Rotemberg, and J. Zou, "Lack of Transparency and Potential Bias in Artificial Intelligence Data Sets and Algorithms," *JAMA Dermatology*, vol. 157, no. 11, p. 1362, Nov. 2021, doi: 10.1001/jamadermatol.2021.3129.

[75] D. Tamboli, A. Topham, N. Singh, and A. D. Singh, "Retinoblastoma: A SEER Dataset Evaluation for Treatment Patterns, Survival, and Second Malignant Neoplasms," *Am. J. Ophthalmol.*, vol. 160, no. 5, pp. 953–958, Nov. 2015, doi: 10.1016/j.ajo.2015.07.037.

[76] P. Tschandl, "Risk of Bias and Error From Data Sets Used for Dermatologic Artificial Intelligence," *JAMA Dermatology*, vol. 157, no. 11, p. 1271, Nov. 2021, doi: 10.1001/jamadermatol.2021.3128.

[77] E. Tasci, Y. Zhuge, K. Camphausen, and A. V. Krauze, "Bias and Class Imbalance in Oncologic Data—Towards Inclusive and Transferrable AI in Large Scale Oncology Data Sets," *Cancers (Basel).*, vol. 14, no. 12, p. 2897, Jun. 2022, doi: 10.3390/cancers14122897.

[78] M. Hägele *et al.*, "Resolving challenges in deep learning-based analyses of histopathological images using explanation methods," *Sci. Rep.*, vol. 10, no. 1, p. 6423, Apr. 2020, doi: 10.1038/s41598-020-62724-2.

[79] A. Bissoto, M. Fornaciali, E. Valle, and S. Avila, "(De) Constructing Bias on Skin Lesion Datasets," in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, IEEE, Jun. 2019, pp. 2766–2774. doi: 10.1109/CVPRW.2019.00335.

[80] M. E. Ahsen, M. U. S. Ayvaci, and S. Raghunathan, "When Algorithmic Predictions Use Human-Generated Data: A Bias-Aware Classification Algorithm for Breast Cancer Diagnosis," *Inf. Syst. Res.*, vol. 30, no. 1, pp. 97–116, Mar. 2019, doi: 10.1287/isre.2018.0789.

[81] C. S. Kruse, R. Goswamy, Y. Raval, and S. Marawi, "Challenges and Opportunities of Big Data in Health Care: A Systematic Review," *JMIR Med. Informatics*, vol. 4, no. 4, p. e38, Nov. 2016, doi: 10.2196/medinform.5359.

[82] S. Datta *et al.*, "Reinforcement learning in surgery," *Surgery*, vol. 170, no. 1, pp. 329–332, Jul. 2021, doi: 10.1016/j.surg.2020.11.040.

[83] H. Mowafi, K. Nowak, and K. Hein, "Facing the Challenges in Human Resources for Humanitarian Health," *Prehosp. Disaster Med.*, vol. 22, no. 5, pp. 351–359, Oct. 2007, doi: 10.1017/S1049023X00005057.

[84] C. J. Kelly, A. Karthikesalingam, M. Suleyman, G. Corrado, and D. King, "Key challenges for delivering clinical impact with artificial intelligence," *BMC Med.*, vol. 17, no. 1, p. 195, Dec. 2019, doi: 10.1186/s12916-019-1426-2.

[85] T. Ching *et al.*, "Opportunities and obstacles for deep learning in biology and medicine," *J. R. Soc. Interface*, vol. 15, no. 141, p. 20170387, Apr. 2018, doi: 10.1098/rsif.2017.0387.

[86] E. Badidi, "Edge AI for Early Detection of Chronic Diseases and the Spread of Infectious Diseases: Opportunities, Challenges, and Future Directions," *Futur. Internet*, vol. 15, no. 11, p. 370, Nov. 2023, doi: 10.3390/fi15110370.

[87] R. I. Mukhamediev *et al.*, "Review of Artificial Intelligence and Machine Learning Technologies: Classification, Restrictions, Opportunities and Challenges," *Mathematics*, vol. 10, no. 15, p. 2552, Jul. 2022, doi: 10.3390/math10152552.

[88] R. Challen, J. Denny, M. Pitt, L. Gompels, T. Edwards, and K. Tsaneva-Atanasova, "Artificial intelligence, bias and clinical safety," *BMJ Qual. Saf.*, vol. 28, no. 3, pp. 231–237, Mar. 2019, doi: 10.1136/bmjqs-2018-008370.

[89] D. S. Char, N. H. Shah, and D. Magnus, "Implementing Machine Learning in Health Care — Addressing Ethical Challenges," *N. Engl. J. Med.*, vol. 378, no. 11, pp. 981–983, Mar. 2018, doi: 10.1056/NEJMp1714229.

[90] A. L'Heureux, K. Grolinger, H. F. Elyamany, and M. A. M. Capretz, "Machine Learning With Big Data: Challenges and Approaches," *IEEE Access*, vol. 5, pp. 7776–7797, 2017, doi: 10.1109/ACCESS.2017.2696365.

[91] A. Cambon-Thomsen, E. Rial-Sebbag, and B. M. Knoppers, "Trends in ethical and legal frameworks for the use of human biobanks," *Eur. Respir. J.*, vol. 30, no. 2, pp. 373–382, Aug. 2007, doi: 10.1183/09031936.00165006.

[92] M. Saria Allahham, A. Awad Abdellatif, A. Mohamed, A. Erbad, E. Yaacoub, and M. Guizani, "I-SEE: Intelligent, Secure, and Energy-Efficient Techniques for Medical Data Transmission Using Deep Reinforcement Learning,"

IEEE Internet Things J., vol. 8, no. 8, pp. 6454–6468, Apr. 2021, doi: 10.1109/JIOT.2020.3027048.
[93] A. Sajid and H. Abbas, "Data Privacy in Cloud-assisted Healthcare Systems: State of the Art and Future Challenges," *J. Med. Syst.*, vol. 40, no. 6, p. 155, Jun. 2016, doi: 10.1007/s10916-016-0509-2.
[94] G. Stiglic, P. Kocbek, N. Fijacko, M. Zitnik, K. Verbert, and L. Cilar, "Interpretability of machine learning-based prediction models in healthcare," *WIREs Data Min. Knowl. Discov.*, vol. 10, no. 5, Sep. 2020, doi: 10.1002/widm.1379.
[95] Y. Wakabayashi, H. Matsui, K. Ikai, M. Hayashi, H. Wakabayashi, and K. Yamamoto, "Developing a Practical Method for Validation of Computerized Systems Integrated With Smart and/or Wearable Devices for Regulatory Compliance of Clinical Trials," *Ther. Innov. Regul. Sci.*, vol. 51, no. 1, pp. 118–124, Jan. 2017, doi: 10.1177/2168479016666585.
[96] H. Kupwade Patil and R. Seshadri, "Big Data Security and Privacy Issues in Healthcare," in *2014 IEEE International Congress on Big Data*, IEEE, Jun. 2014, pp. 762–765. doi: 10.1109/BigData.Congress.2014.112.
[97] J. K. Bower, S. Patel, J. E. Rudy, and A. S. Felix, "Addressing Bias in Electronic Health Record-based Surveillance of Cardiovascular Disease Risk: Finding the Signal Through the Noise," *Curr. Epidemiol. Reports*, vol. 4, no. 4, pp. 346–352, Dec. 2017, doi: 10.1007/s40471-017-0130-z.
[98] F. Ali *et al.*, "A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion," *Inf. Fusion*, vol. 63, pp. 208–222, Nov. 2020, doi: 10.1016/j.inffus.2020.06.008.
[99] F. Zeshan and R. Mohamad, "Medical Ontology in the Dynamic Healthcare Environment," *Procedia Comput. Sci.*, vol. 10, pp. 340–348, 2012, doi: 10.1016/j.procs.2012.06.045.
[100] Y. Carlisle, "Complexity dynamics: Managerialism and undesirable emergence in healthcare organizations," *J. Med. Mark. Device, Diagnostic Pharm. Mark.*, vol. 11, no. 4, pp. 284–293, Nov. 2011, doi: 10.1177/1745790411424972.
[101] M. Ienca and E. Vayena, "On the responsible use of digital data to tackle the COVID-19 pandemic," *Nat. Med.*, vol. 26, no. 4, pp. 463–464, Apr. 2020, doi: 10.1038/s41591-020-0832-5.
[102] P. E. Petersen and T. Yamamoto, "Improving the oral health of older people: the approach of the WHO Global Oral Health Programme," *Community Dent. Oral Epidemiol.*, vol. 33, no. 2, pp. 81–92, Apr. 2005, doi: 10.1111/j.1600-0528.2004.00219.x.
[103] M. R. Hussain *et al.*, "Effective cost optimization approach in Healthcare to Minimize the treatment cost of Brain-tumor Patients," in *2019 International Conference on Computer and Information Sciences (ICCIS)*, IEEE, Apr. 2019, pp. 1–5. doi: 10.1109/ICCISci.2019.8716459.
[104] Y. You and Z. Hua, "An intelligent intervention strategy for patients to prevent chronic complications based on reinforcement learning," *Inf. Sci. (Ny).*, vol. 612, pp. 1045–1065, Oct. 2022, doi: 10.1016/j.ins.2022.07.080.
[105] S. Chen *et al.*, "Reinforcement Learning Based Diagnosis and Prediction for COVID-19 by Optimizing a Mixed Cost Function From CT Images," *IEEE J. Biomed. Heal. Informatics*, vol. 26, no. 11, pp. 5344–5354, Nov. 2022, doi: 10.1109/JBHI.2022.3197666.
[106] W. Nie *et al.*, "Deep reinforcement learning framework for thoracic diseases classification via prior knowledge guidance," *Comput. Med. Imaging Graph.*, vol. 108, p. 102277, Sep. 2023, doi: 10.1016/j.compmedimag.2023.102277.
[107] S. M. Barros Netto, V. R. Coelho Leite, A. Correa, A. C. de Paiva, and A. de Almeida Neto, "Application on Reinforcement Learning for Diagnosis Based on Medical Image," in *Reinforcement Learning*, I-Tech Education and Publishing, 2008. doi: 10.5772/5291.
[108] B. Smith, "Bias in Reinforcement Learning: Lessons Learned and Future Directions in Healthcare Applications," *researchgate.net*, pp. 1–22, 2022.
[109] D. Karimi, H. Dou, S. K. Warfield, and A. Gholipour, "Deep learning with noisy labels: Exploring techniques and remedies in medical image analysis," *Med. Image Anal.*, vol. 65, p. 101759, Oct. 2020, doi: 10.1016/j.media.2020.101759.
[110] P. Henderson, R. Islam, P. Bachman, J. Pineau, D. Precup, and D. Meger, "Deep Reinforcement Learning That Matters," *Proc. AAAI Conf. Artif. Intell.*, vol. 32, no. 1, Apr. 2018, doi: 10.1609/aaai.v32i1.11694.
[111] D. Abel *et al.*, "On the Expressivity of Markov Reward," Nov. 2021, Available: http://arxiv.org/abs/2111.00876
[112] Q. Liu, L. Li, Z. Tang, and D. Zhou, "Breaking the Curse of Horizon: Infinite-Horizon Off-Policy Estimation," Oct. 2018, Available: http://arxiv.org/abs/1810.12429
[113] G. Dulac-Arnold *et al.*, "Challenges of real-world reinforcement learning: definitions, benchmarks and analysis," *Mach. Learn.*, vol. 110, no. 9, pp. 2419–2468, Sep. 2021, doi: 10.1007/s10994-021-05961-4.
[114] S. Rome, T. Chen, M. Kreisel, and D. Zhou, "Lessons on off-policy methods from a notification component of a chatbot," *Mach. Learn.*, vol. 110, no. 9, pp. 2577–2602, Sep. 2021, doi: 10.1007/s10994-021-05978-9.
[115] N. Karampatziakis, S. Kochman, J. Huang, P. Mineiro, K. Osborne, and W. Chen, "Lessons from Contextual Bandit Learning in a Customer Support Bot," May 2019, Available: http://arxiv.org/abs/1905.02219
[116] Y. Li, "Reinforcement Learning in Practice: Opportunities and Challenges," Feb. 2022, Available: http://arxiv.org/abs/2202.11296

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