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Original Article

Ethical and Privacy Issues in the Use of Machine Learning for Personalized Care for Elderly Patients

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***Abstract** - Machine learning presents various advantages when used in care personalization for the elderly. However, it also raises ethical and data privacy problems that must be addressed. The primary focus of this research is to present a comparative analysis of ethical and privacy issues in machine learning and traditional big data analytics tools. The qualitative research uses secondary data from past studies to achieve this objective. The main conclusion from the research is that machine learning presents similar ethical and data privacy problems as other tools. However, machine learning offers predictive capabilities that can be used to predict and mitigate these risks. Therefore, some applications of machine learning should be eliminated in geriatrics, especially monitoring and surveillance. Alternatively, these applications should require patients' informed consent.*

***Keywords** - Artificial Intelligence, Big data, Data analytics, Data privacy, Machine learning.*

1. Introduction

Care personalization for the elderly requires using massive amounts of health-related data. However, clinicians face a massive challenge extracting the relevant data, resulting in the widespread deployment of machine learning and related technologies. Machine learning is a subset of Artificial Intelligence (AI) that uses existing data to build analytical models [1]. In geriatric care, machine learning algorithms have proven their effectiveness in predicting care needs among the elderly [2]. Considering the vulnerability of elderly patients, effective and accurate predictions can massively reduce health risks by facilitating the implementation of preventive care.

However, using machine learning raises serious ethical and privacy challenges. Current literature on privacy and ethics in geriatrics focuses on the broader AI, meaning there is inadequate literature focusing on machine learning. This leaves a massive gap that must be addressed, especially because the fundamental differences between AI and machine learning prevent the two terminologies from being used interchangeably in this regard. There is a significant gap regarding the lack of adequate literature on how machine learning is deployed in care personalization. The gap arises from the fact that machine learning is a relatively novel technology in healthcare, and many practitioners have zero experience with machine learning. If practitioners do not understand a technology, then there is a possibility they will not adopt it.

However, the main research gap involves the lack of ethical and privacy frameworks deployed to the specific use of machine learning in healthcare and other industries. Essentially, many institutions struggle in their attempt to apply existing frameworks to machine learning. Their efforts often fail because of the broad nature of machine learning applications. If the organizations do not understand the ethical and privacy risks involved, there is a high likelihood that they will choose not to develop and deploy machine learning models. Considering the potential benefits of machine learning, privacy and ethical challenges remain the biggest barriers to the full adoption of most AI solutions. The research gap is also manifested in academia, where scholars have failed to articulate ethical and privacy frameworks specifically for machine learning applications. Only a few studies have established that reliance on existing frameworks is a massive problem and outlined the necessity for developing new laws and regulations for machine learning. This is despite many scholars addressing the subject of ethics and privacy revolving around the use of sensitive patient data.

The focus of this research is to examine the ethical and privacy issues arising from machine learning usage in personalizing care for the elderly. Considering that there are hardly other studies on the subject, this research is relatively novel, and seeks to lay the foundation for future research. After outlining the ethical and privacy challenges, the research will offer a critical examination of the proposed solutions. The purpose of such an examination is to make a case for treating machine learning and other AI applications differently from other technologies by proving that most novel solutions work and that the current compliance and regulatory frameworks are impractical for machine learning applications. To achieve this objective, the study answers the following research questions:

- How does machine learning affect privacy and ethics in geriatrics?
- How do the ethical and privacy implications compare with traditional predictive analytics tools like IBM SPSS?
- What are the potential solutions to the ethical and privacy challenges of using machine learning for customizing care for the elderly?

2. Literature Review

The primary concern and goal in geriatrics is effective prevention and early detection. As a standard of care, this approach compels physicians to critically screen data from various sources and apply the findings to develop individual healthcare goals for elderly patients [3]. Predictive analytics tools are critical in helping personalize care for the elderly.

Recent technological advancements have seen the proliferation of machine learning, which has been applied across all areas where data management is involved. Machine learning algorithms help link health-related data from various sources, including online (web and social media), connected devices, and the Internet of Things (IoTs). The data is majorly used for predictive purposes**,** which help personalize care. For example, the data can be used to predict patient behaviors, track data to facilitate diagnosis and monitor care progression [4]. The main types of machine learning are illustrated in figure below, derived from Peng et al. [1]**:**

All technologies used in healthcare raise ethical and privacy concerns. Current literature has illustrated the various ways in which all AI-related technologies affect practice ethics and data and patient privacy. Literature specific to machine learning also focuses on the broader healthcare practice and hardly on geriatrics. For example, in the study by [3], most of the machine learning standards have been designed primarily to address the ethical problems associated with the technology. Additionally, machine learning in geriatrics and other healthcare practices is governed by legal and ethical norms that focus on the collection, usage, storage, and transfer of data [3]. Machine learning is also a critical component of the robotics used in healthcare. Some commentators believe that it is impossible to teach ethics to a machine. Therefore, it is considered unethical for machine learning to be used to replace rather than supplement humans in geriatrics [5]. The rationale is that social interaction is a critical component of caring for the elderly. Using machine learning and related technologies in geriatrics also poses more ethical issues, including ethical consent. Even though machine learning helps develop robotics that can perform all human-like functions, designers have failed to address the ethical issues. This will not happen until machine learning can develop the proper algorithms for this purpose. Similarly, using machine learning-based technologies may require informed consent, another sensitive ethical issue [3].

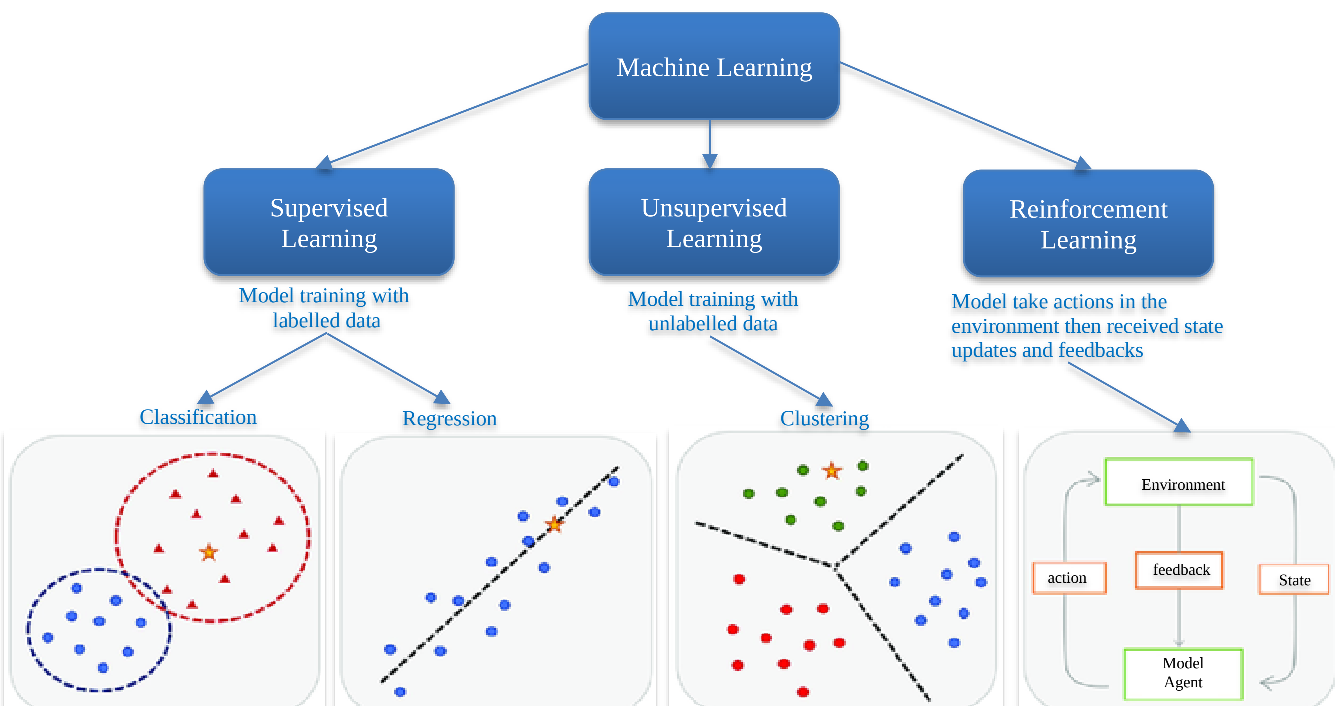

Fig. 1 Main types of and approaches to machine learning

However, the main application of machine learning in geriatrics and other healthcare practices involves data management. Machine learning uses algorithms that link health-related data to help make predictions based on past data [6]. For example, individuals' online behaviors on the web can be examined using machine learning algorithms to predict future behaviors and disease diagnoses. Outcome data from various databases can also be examined in the same way using the algorithms [4]. Such data, often comprising patient data, requires careful handling to avoid the legal implications of a breach of privacy rules.

Issues of data privacy in machine learning are wide-ranging and often spill over to other healthcare technologies. Most notably, machine learning is used along with other technologies involved in the collection, storage, transfer, and use of data, including the Internet of Things (IoTs). IoTs in many applications comprise interconnected devices and smart services that collect data and transfer it to a cloud for storage and retrieval by the relevant devices and users [7]. IoTs have inherent privacy problems, which could spill over to machine learning when its algorithms are used for managing such data. However, there are instances where studies examine how machine learning can be used as a solution to the privacy challenges facing IoTs. Using analytical and predictive algorithms, machine learning can analyze and predict architectural behavior, simulate real-world privacy-related malware, accurately detect malicious activity against privacy, and facilitate early warning signs as a basis for privacy-related risk management protocols [8]. Therefore, it cannot be assumed that machine learning will always exacerbate privacy problems when used in geriatrics.

Caring for the elderly is a practice that requires close and constant monitoring to prevent such events as falling. Without the use of modern technologies, this practice would require dedicated personal attention, which can take a toll on organizational human resources. Machine learning and other technologies are critical in monitoring and surveillance, but they have raised serious ethical and privacy dilemmas [9][10]. Scholars believe that machine learning technologies may be a marvel, but one that is yet to be subjected to proper research regarding how it affects security and privacy [10]. This is because, despite the need for monitoring and surveillance, elderly people are entitled to independent living and the right to privacy [9]. It would be unethical if care facilities ignore these considerations even if they were to achieve effective and efficient predictive models that help achieve a 100% fall-free environment for elderly patients.

Data in healthcare has always raised ethical and privacy issues, even when classic technologies and tools have been used. The issue of big data is the main trigger point of ethical and privacy problems, especially big data analytics. The tools adopted to ease these problems have continuously exposed security vulnerabilities in data management in healthcare.

Even when many countries globally implemented legislation upholding the privacy of individuals, institutions still face the risk of breaches and unethical practices [11]. Current literature does not address how older technologies, for instance, IBM SPSS software, affected data management in geriatrics and the ethical and privacy implications of such technologies. However, much of the literature focused on broader perspectives regarding how technologies were used and their implications on ethics and privacy. Most of these studies often warned of such emerging issues as open-source technologies for informatics and research [12]. Therefore, it is possible to conclude that technologies on their own are not the cause of the ethical and privacy problems. Rather, the human interactions with these technologies and the nature of their use threaten privacy and raise ethical concerns.

There is an emerging body of literature on the ethical and privacy issues in the use of machine learning in general applications and healthcare. The proliferation of AI applications and AI-driven decision-making necessitates such studies. Machine learning approaches are considered one of the typologies of algorithms underpinning AI and are often developed as black boxes [24]. As such, the machine learning code scripts are hardly scrutinized, which raises serious ethical and privacy risks. Ethical questions arise regarding the extent to which stakeholders' consent and input are considered in such applications, especially those involving the automation of decision-making.

The rationale is that machine learning applications will engage in data access and processing. Many studies on ethical issues in machine learning apply data processing-centered ethical analysis, which focuses on privacy and data governance [25]. Such approaches allow for stringent analysis of the legal aspects alongside the data regulations such as the General Data Protection (GDPR). Ethical aspects in these contexts are addressed from a legal perspective, where scholars establish that without social awareness and responsibility, laws alone cannot guarantee socially compliant information technology. Recent research on ethical and privacy issues in the application of machine learning in healthcare indicates that the industry experiences several serious ethical and regulatory challenges. According to Basu et al. [26], such challenges revolve around fairness, privacy, transparency, accountability, and conflicts of interest. Only by addressing these issues will machine learning bring positive results in healthcare. Like other technologies in healthcare, data privacy arises from the use of patient data in electronic health records and other data storage and sources. Globally, countries and regions have developed data protection guidelines. For example, the GDPR was developed in the European Union (EU), while the United States has the Health Insurance Probability and Accountability Act (HIPAA) [26]. Even with these regulations, data breaches in healthcare remain a serious problem, meaning that data privacy is a problem that is yet to be resolved.

Identifying ethical considerations in using machine learning in healthcare also poses a challenge. The rationale is that the impacts of machine learning and other emerging technologies remain uncertain [27]. Additionally, many ethical frameworks focus on articulating guiding principles without systematically establishing the potential problems. For example, many scholars assume that machine learning poses similar data privacy issues to other healthcare technologies. However, the fact that machine learning is not fully integrated into the healthcare system means its impacts are not fully understood. Other challenges in establishing ethical considerations in machine learning include the diversity of stakeholders, highly restricted focus, the breadth of applications, and the exceptionalism of AI and machine learning [27]. According to [28], machine learning in healthcare applications can range from fully autonomous AI diagnosis to non-autonomous predictive models and healthcare resource allocation models. Such a wide range of applications makes it challenging to develop an ethical framework that accommodates all applications.

3. Methods

3.1. Approach and Design

The study is qualitative research that relies on secondary data from various sources. Qualitative studies are effective in answering the question of why something is observed, facilitating interventional improvement, and examining complex multicomponent interventions [13]. This research examines privacy and ethical issues in the use of machine learning in geriatrics to help develop relevant interventions. In terms of design, the study will be a comparative analysis that seeks to examine differences and similarities between research variables in the context of the research. In this case, the ethical and privacy issues of machine learning are examined against the backdrop of the technologies it replaces in personalizing care for elderly patients. Since it is a comparative analysis, the selected design option is observational descriptive research.

3.2. Quality Criteria in and Sampling Bias

Even though the study uses secondary data, it is important to consider issues of quality and bias. In many qualitative studies, sample equivalence entails an equal selection of respondents or sources. In this case, sampling bias is eliminated by subjecting all sources to inclusion and exclusion criteria. The selected criteria should ensure that the researcher only uses sources that qualify for selection and leaves out the rest. The risk of bias can be assessed using various research tools, including systematic review. The most common among these tools is the Cochrane Collaboration tool attributed to Higgins and Altman. The tool comprises criteria or a set of questions with responses of Yes, No, or Unclear. The criteria are used to develop a weighted score, where the sources that score the lowest are considered low quality. However, a newer version of the Cochrane Collaboration tool was developed to offer a more comprehensive framework for assessing the risk of bias. Figure 2 below presents the adapted Cochrane Collaboration tool summarizing how the risk of bias is assessed [23]**:**

Cochrane Collaboration's tool for assessing risk of bias (adapted from Higgins and Altman13)

Bias domain	Source of bias	Support for judgment	Review authors' judgment (assess as low, unclear or high risk of bias)
Selection bias	Random sequence generation	Describe the method used to generate the allocation sequence in sufficient detail to allow an assessment of whether it should produce comparable groups	Selection bias (biased allocation to interventions) due to inadequate generation of a randomised sequence
	Allocation concealment	Describe the method used to conceal the allocation sequence in sufficient detail to determine whether intervention allocations could have been foreseen before or during enrolment	Selection bias (biased allocation to interventions) due to inadequate concealment of allocations before assignment
Performance bias	Blinding of participants and personnel'	Describe all measures used, if any, to blind trial participants and researchers from knowledge of which intervention a participant received. Provide any information relating to whether the intended blinding was effective	Performance bias due to knowledge of the allocated interventions by participants and personnel during the study
Detection bias	Blinding of outcome assessment'	Describe all measures used, if any, to blind outcome assessment from knowledge of which intervention a participant received. Provide any information relating to whether the intended blinding was effective	Detection bias due to knowledge of the allocated interventions by outcome assessment
Attrition bias	Incomplete outcome data'	Describe the completeness of outcome data for each main outcome, including attrition and exclusions from the analysis. State whether attrition and exclusions were reported, the numbers in each intervention group (compared with total randomised participants), reasons for attrition or exclusions where reported, and any reinclusions in analyses for the review	Attrition bias due to amount, nature, or handling of incomplete outcome data
Reporting bias	Selective reporting	State how selective outcome reporting was examined and what was found	Reporting bias due to selective outcome reporting
Other bias	Anything else, ideally prespecified	State any important concerns about bias not covered in the other domains in the tool	Bias due to problems not covered elsewhere

*Assessments should be made for each main outcome or class of outcomes.

Fig. 2 Summary of Cochrane Collaboration tool for risk bias

Domain	Criteria explanation	Indicative questions
Rigour in research conduct	Judgement on how carefully the research is carried out; tends to be a judgement of reporting quality	Is the research question clearly defined? Rationale for the study design discussed? Is a sampling strategy well defined and justified? Is the method of data collection clearly described?
Study context	A detailed description is needed to judge wider applicability of the findings; refers to transferability	Detailed description of the context of the study to allow assessment of applicability to other settings? Discussion of limits to wider inference?
Analysis procedure	An important component of rigour and reliability	Is the method of analysis clearly described?
Credibility	Judgement on how well the findings are presented and how meaningful or believable they are	How credible are the findings? Are the claims made supported by sufficient evidence?
Depth, detail & richness of findings	An indication of the quality of the analysis which underlies credibility claims	E.g. "thick vs. thin description"? Illumination of multiple perspectives/contribution of sample design? Detection of underlying factors/influences or conceptual linkages? Presentation of illuminating extracts/observations?
Contribution to knowledge	Judgement on the relevance and potential utility of the findings in relation to policy, practice or theory	Clear discussion of how the research findings contribute to:Understanding of uptake of malaria preventive interventions by pregnant women?; theoretical conceptions of uptake of malaria preventive interventions in pregnancy? New areas of investigation identified?

Fig. 3 Quality criteria for the research

The quality of the research also depends on the approaches taken, designs selected, and the sources included. In this case, the quality of the research focuses on the broader methodological approach to research. The research is rigorous and remains within the scope and context outlined in the problem statement and research questions.

Most importantly, the research contributes significantly to knowledge of the subject, in this case, privacy and ethical implications of machine learning use in geriatrics. The quality criteria followed in this research are summarized in Figure 3 below, adapted from Atkins et al. [21]**:**

3.3. *Data Collection and Analysis*

3.3.1. Data Collection

The data is collected from various secondary sources, preferably peer-reviewed journal articles, government and non-governmental organizations' reports, and reliable and credible news articles and reports on ethical and privacy issues involving machine learning. The data that needs to be collected is specified in the research purpose and the inclusion and exclusion criteria below.

The most important point to note is that the secondary data comes in many forms, including expert commentaries and findings of past research studies. The data must help answer the three research questions. The search strategy for the data also includes the use of specified keywords that help generate the best results. For each research question, a set of keywords will be used to search for materials, which will then be subjected to the relevant criteria.

Several keywords were designed to help generate the desired results. Examples of major keywords included ethical implications of machine learning in geriatrics, privacy issues in the use of machine learning in geriatrics, and machine learning in care personalization for elderly patients.

Several journals were searched using these keywords, including Springer, Sage Open, MDPI, The BMC, and JAMA. However, the initial search was conducted on Google Scholar, which produced a large number of open-access peer-reviewed journal articles.

3.3.2. Inclusion and Exclusion Criteria

The inclusion criteria include currency, relevance, and authority. Currency entails how recently the source was published. In this case, sources not older than five years are preferred. Relevance entails the extent to which the source addressed the subject matter of the research. All sources included in the study must explore ethical and/or privacy issues in machine learning in geriatrics.

The authority will be examined regarding the credibility and expertise of the authors or the publisher. Preferably, authors must be experts in the field, and the publishers must be credible. A qualitative content analysis is used to examine the data and draw the necessary conclusions.

Table 1. Sample findings from included sources

Source Citation	Source Type	Key Findings/Conclusions
Babic et al. [14]	Online article	Machine learning depends on so many parameters and human input that could change how it makes decisions. It could lead to wrong decisions with serious implications.
Lee et al. [15]	Online article	Machine learning algorithms are capable of making biased decisions based on given data.
Yousuf [16]	News article	Involving old people when designing machine learning-related tools helps alleviate ethical concerns about such tools.
Ruf et al. [17]	Conference paper	Machine learning in geriatrics should only be used to complement and not replace human care.
Strang and Sun [11]	Peer-reviewed research paper	Big data analytics tools raise ethical and privacy issues depending on how people use them.
Kobayashi et al. [12]	Peer-reviewed research paper	Open data in geriatrics and other healthcare settings is prone to privacy and ethical problems.
Ho [9]	Peer-reviewed research paper	Monitoring and surveillance applications of machine learning have the potential to breach patient privacy.
El-Gendy et al. [8]	Peer-reviewed research paper	Machine learning helps reduce the privacy and security threats in IoTs.
Yang [10]	Peer-reviewed research paper	Machine learning and IoTs pose privacy challenges when used for surveillance purposes in geriatrics.
Choudhury et al. [3]	Peer-reviewed research paper	Many machine learning standards have been designed to address legal and ethical challenges posed by machine learning.

3.3.3. Coding and Qualitative Content Analysis

Qualitative content analysis can be described as standardized methods that use technical tools for basic, superficial, and simple sorting of research data. Even though qualitative content analysis may lack depth and rigor, it helps examine evidence regarding the research phenomena. In this case, the content analysis works well with a descriptive comparative analysis because it allows the researcher to describe the comparative data in great depth.

The codes are built around the research questions, which give out three themes: privacy and ethical issues in machine learning, comparing machine learning with traditional technologies, and potential solutions to the ethical and privacy challenges. The findings will be presented as a narrative analysis covering privacy and ethical implications of machine learning, a comparison of the same with other older technologies, and potential solutions to ethical and privacy issues affecting machine learning in geriatrics.

4. Results and Discussion

The search resulted in tens of sources using the various keywords designed based on the research topic. However, the main challenge was that an overwhelming majority of the results yielded results generalizing AI, regardless of how much the keywords were improved. As such, screening many such sources was necessary to determine if they addressed machine learning in their contents. Sufficient discussions of machine learning and its relationship to ethics and privacy allowed such sources to pass the inclusion criteria. However, most were disqualified because they had a superficial discussion of the subject. A summary of the findings from sampled sources is presented in Table 1.

4.1. Description of Tools and Sources

Various keywords were designed to help with the search for secondary sources of data. In this case, the main keywords included “ethical and privacy challenges of machine learning in geriatrics,” “ethical challenges of machine learning in care personalization for the elderly”, “privacy challenges of machine learning in care personalization for the elderly”, and ethical and privacy implications of machine learning versus data analytics tools in geriatrics.” Further searches were conducted by modifying the initial keywords to produce new phrases or even sentences that helped narrow down the search to the specific content. The search strategy resulted in over 300 sources whose abstracts or contents discussed the ethical and/or privacy implications of machine learning in geriatrics. However, the search initially produced over 500 sources on the general subject of ethical and privacy issues in machine learning without specifying care personalization for the elderly. In this list were also other sources that discussed ethical and privacy issues in artificial intelligence, with only a brief mention of machine learning. The initial screening eliminated all sources that failed to mention geriatrics and machine learning. The 300 sources were taken through further screening to include the other inclusion and exclusion criteria. This resulted in over 28% of the sources being eliminated, leaving only 216 credible and relevant sources. Of these, 95% were past studies on the same subject, while 1.5% examined ethical and privacy issues in older data analytics technologies. About 84% of the sources were systematic reviews and metaanalyses, 13% were empirical studies, and the rest could be considered grey literature. The newer version of the Cochrane Collaboration was used to eliminate the risk of bias. Rather than the nine questions and their weights used in the previous model, the newer version offered a more comprehensive mechanism. However, the new version focuses majorly on randomized trials, but it had aspects that were usable in this qualitative study. The main areas of bias in the new model include the randomization process, deviation from intended interventions, missing outcome data, measurement of outcome, and selection of the reported result. The aspects that were assessed in this research were modified elements of the tool, including measurement of research outcome, bias in the source selection process, deviation from the intended objective, and missing out on data. After assessing all included sources, it was established that the highest quality sources were those that remained specific to ethical and privacy issues of machine learning. The lower quality sources mentioned machine learning as a subset of AI, but whose content was deemed relevant and adequate for use in this research.

4.2. Privacy and Ethical Issues in Machine Learning

The current studies have made an irrefutable claim that machine learning raises critical ethical and privacy issues. Much of the data obtained from this study focuses on the use of machine learning in areas of decision-making and data management. Caring for elderly patients often involves preventing such events as falling, which require constant monitoring. Machine learning is used to build monitoring and surveillance tools that keep track of movements and other activities. The main challenge with such an approach is that surveillance entails keeping an eye on people, even in private. As a result, elderly patients' privacy is breached. Regarding data management, machine learning is used to gather and screen data and is sometimes used alongside the IoTs. In such a setup, machine learning raises many ethical concerns, including the potential for biased decisions founded on data and privacy breaches due to the vulnerability of IoTs.

However, the research has also established that machine learning has highly effective predictive analytics that can detect and address vulnerabilities, making even the IoTs safer. In this regard, it can be concluded that machine learning can be both a challenge and a solution to privacy and practice ethics, depending on how and where it is used.

4.3. Comparing Machine Learning with Older Technologies

The comparison between machine learning and older technologies considers the fundamental differences between the two and the implications for ethics and privacy. It is important to explain the fundamental differences to understand how the two work. Traditional technologies can be considered tools for data science, defined by IBM as a multidisciplinary field involving extracting value from massive data [18]. In other words, data science uses advanced tools to examine raw data, process it, and develop such insights as statistics, models, and data analytics. Machine learning could also be part of data science, but it is more advanced and is used differently. In essence, while data science is about bringing structure to data, machine learning seeks to learn from the data itself. Therefore, traditional technologies help access and manipulate data, similar to how machine learning is used. In such a case, the two categories of analytics and data management tools would have similar ethical and privacy implications. The rationale for the above observation is that traditional tools and machine learning have access to big data, meaning they all have to deal with issues of disclosure and access. There is a disclosure risk with a major legal implication in both cases. All big data analytics tools, traditional and modern, must operate within the legal frameworks governing privacy, including the GDPR. The rules dictate that personal data should be processed in ways that facilitate security and confidentiality [19]. From a legal perspective, the nature and type of the data analytics tools do not matter as long as the rules are observed. The main concern and potential for differences is that both categories require access to data, meaning the main risk lies with how the data is handled and where the vulnerabilities are. In many cases, the human connection becomes the greatest risk in data management.

Recent studies indicate that ethical and privacy issues lie with the data because data contains sensitive private information. Regarding the IT systems, the vulnerability lies with the openness of the health datasets [12]. Therefore, both traditional and machine learning tools must be used in a manner that restricts such openness through such approaches as access controls and data-sharing protocols. Legislations on data privacy cut across all IT systems because they all present similar levels of risk. For example, the Health Insurance Portability and Accountability Act (HIPAA) focuses on all types of big data analytics tools and other IT infrastructure [11]. However, some studies indicate that the predictive capabilities of machine learning can help predict and mitigate risks in big data [20]. Traditional tools lack such capability, making machine learning the ultimate approach to ethical practice and data protection in geriatrics.

Table 2 presents a comparative analysis table that sums up the findings on the comparison between machine learning and older analytics technologies regarding privacy and ethical concerns.

4.4. Potential Solutions to Ethical and Privacy Challenges of Machine Learning in Geriatric

From the comparative analysis and the narrative syntheses on the privacy and ethical issues, the main observation is that the technologies are critical in geriatrics and that the manner and nature of their use raises ethical and privacy issues. The research findings have revealed that both machine learning and older data analytics tools require access to patient data, which is used to generate insights.

Table 2. Comparative analysis of machine learning versus older technologies

Issue	Machine Learning	Older Technologies
Ethics	-Use of sensitive data -Compliance with ethical standards	-Use of sensitive data -Compliance with ethical standards
Privacy	-Data leak threats -Unauthorized access	-Data leak threats -Unauthorized access
Data Access	-Access controls	-Access controls
Data Sharing	-Vulnerability of data	-Vulnerability of data
IoT Connection	-Increases risk -Could be used to mitigate risk	-Increases risks -No predictive capabilities to help mitigate the risks
Informed consent	-Necessary in certain contexts	-Hardly required

The access to the data can be regulated such that only authorized personnel have access to the sensitive information. The research has also established that the weakest link in the privacy issue is the human connection. This means that the first approach to resolving ethical and privacy issues with machine learning should be managing the human connection. Trust among the people using machine learning is a critical step in this regard [22]. If users are trustworthy, responsible, and accountable, they behave in a manner that does not endanger the privacy of the patient data.

The research findings also highlight that the access controls should not focus only on internal users. For instance, wearable devices are handled by practitioners, but the data they gather and store could be accessed by external individuals, especially when such data is made available online [4]. However, it is important to understand that this is not a problem for machine learning tools. Rather, it is a problem of other tools and devices used in handling and managing patient data. The main concern is that when machine learning is used to access and transfer data to other tools or online resources, the access connections between the machine learning and other tools should be made safe such that leakages and breaches are eliminated.

Another key concern for the ethical and privacy issues with machine learning in geriatrics is the IoT. Since the IoTs are inherently vulnerable to cyber-attacks and other malicious activity, they transfer the same risks to machine learning tools. This means that when machine learning is working with IoTs, the safety of its tools depends on the safety of the IoTs themselves. Findings from this research confirm that protecting IoTs from malware and attacks will help machine learning tools operate without privacy and ethical complications [8].

4.4.1. Explainable, Trustworthy, Ethical Machine Learning

Despite the challenges in identifying ethical challenges in machine learning, this research has established that many scholars still manage to offer recommendations and opinions on what could make machine learning and its use in healthcare ethical. According to Rasheed et al. [29], the black-box nature of machine learning prevents widespread adoption by clinicians.

Therefore, there is a need to offer explanations regarding the decisions of the models to enhance trust and transparency. This leads to the emergence of the concept of explainable machine learning (XML). Explainability entails the production of explainable models while still maintaining high prediction results, which helps users understand and trust the decisions of the machine learning applications. Explainability is sometimes used synonymously with interpretability, a concept often used to imply making machine learning more transparent [30]. Across both terminologies, the scholars seek to ensure that users comprehend the machine learning and other AI models (including deep learning and deep neural networks), their functionality, and their output. The end goal is to ensure that users can trust the models.

Ethical machine learning is another emergent concept whose notion is implementing measures that make machine learning ethical. Examples of such measures established in this research include social justice [31]. These studies emphasize that ethical machine learning meets various social justice standards, including those that touch on healthcare costs and clinical diagnosis.

4.4.2. Transparency, Fairness, and Accountability

Transparency, fairness, and accountability have also emerged as core themes and measures of the ethical use of machine learning in healthcare and other settings. Transparency can be achieved through explainable/interpretable machine learning [29] [30]. However, achieving transparency poses a serious problem because machine learning models can be extremely complex such that explaining them to healthcare practitioners is impossible [26].

Accountability entails a relationship where one party has an obligation to justify actions. In this case, machine learning developers can pursue accountability by justifying their choices of machine learning models and the privacy, legal, and ethical risks involved. Lastly, fairness revolves around selective biases regarding measurements, data collection, and missing values. Essentially, machine learning models are fair when they eliminate these biases. Therefore, machine learning applications are considered ethical when they meet the transparency, fairness, and accountability criteria.

4.4.3. Privacy-Preserving Machine Learning

Another theme that emerged from this research is privacy-preserving machine learning, an idea that machine learning models can be designed such that they preserve the patients' right to privacy. Various frameworks have been developed in this regard. For example, a decentralized, collaborative, and privacy-preserving machine learning for multi-hospital data (DeCaPH) framework proposed by [32] is used to train machine learning models to improve the utility-privacy trade-off, meaning that the models retain high-performance levels while preserving the privacy of the training data. The findings of this study illustrate that the performance only drops by 3.2% compared to models not trained with the DeCaPH framework. Additionally, the vulnerability to privacy risk for the models trained with this framework drops by approximately 16% [32]. The framework makes it possible to collaborate without increasing privacy risks since collaboration significantly improves the performance of models.

Models trained with private data perform less than those trained through collaboration. Other proposed models work in a similar manner – that is, support collaboration while preserving the privacy of sensitive data sets. A study by Sinac et al. [33] experimented with privacy-preserving federated machine learning using FAIR data. The experiment indicated that the proposed solution is effective in leveraging FAIR datasets from multiple organizations for federated machine learning while protecting sensitive health information.

4.4.4. Compliance and Regulatory Frameworks

Compliance and regulatory frameworks present a potential solution to privacy and ethical challenges in machine learning and a major scholarly gap. Current evidence suggests that regulators and institutions across all industries are forced to use the existing regulations, guidance, and standards in designing, developing, releasing, testing, maintaining, and distributing AI and machine learning-enabled devices [34]. The result has been strict controls on change management that regulators and institutions cannot autonomously and dynamically adapt to new data.

Additionally, there has been an overly extensive mapping of iterative algorithm development methods as developers attempt to comply with regulatory requirements. Scholars also express challenges emanating from the lack of harmonized laws or standards specifically regulating machine learning. This is in addition to the fact that the current regulations lag behind the usage of machine learning, causing institutions to struggle with time and resources, attempting to understand how regulations apply to their specific contexts [35]. According to [36], there is a massive uncertainty regarding the specific regulatory requirements for medical machine learning systems. As such, the current compliance and regulatory frameworks are inadequate tools for enhancing privacy and ethical use of machine learning in healthcare.

5. Conclusion

Machine learning is a technology with endless applications in healthcare, including care personalization for the elderly. However, the technology raises several ethical and privacy issues. This research has established that machine learning, like all other tools used in big data analytics, presents a plethora of ethical and data privacy problems that must be addressed. Personalizing care for the elderly requires gathering large volumes of data, some of which may require surveillance and monitoring. Such practices may help predict and prevent health risks, but they also infringe on the privacy of the patients. To arrive at this conclusion, the study has used a combination of tools to gather and analyze the data. The list of tools includes risk bias assessment tools and quality assessment tools. The study uses secondary data from various sources that have been subjected to a screening procedure based on inclusion and exclusion criteria. The narrative analysis focusing on the three main themes present the outcome of the analysis of the data, conducted using a qualitative content analysis. The quality criteria have been observed in a number of areas. First, the research has used credible sources assessed using the Cochrane Collaboration tool. Second, the study is rigorous and confined within the limits of the study context. Lastly, the depth of the research is significant to ensure that the study makes commendable contributions to knowledge.

The primary recommendation is that machine learning should be used only in areas and purposes that do not jeopardize ethical practice and data privacy. Surveillance and continuous monitoring infringe on privacy and should either be abolished or require informed consent from the patients. The findings indicate that despite the weaknesses, the ethical and privacy issues can be eliminated by addressing the human-machine-learning connection because it is the weakest link. Since the ethical and privacy issues emanate from humans and the connection to IoTs, it is recommended that all machine learning applications in geriatrics must have algorithms that protect them from these vulnerabilities. The findings have also indicated that, in some cases, the predictive capabilities of machine learning can help identify and mitigate ethical and privacy issues. Therefore, it is recommended that machine learning tools used in geriatrics should contain such algorithms that help identify threats in data and help design and implement proper protocols for data protection.

Most importantly, machine learning should not be treated to the same ethical and privacy regulations as other technologies. New regulations and compliance frameworks are a necessity for the healthcare industry to successfully exploit the benefits of machine learning applications. Many of the proposed and novel solutions are evidently practical. Therefore, the remaining barrier is the compliance and regulatory frameworks that are not designed for machine learning. Making this change unlocks endless possibilities for machine learning use in healthcare settings.

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