Navigating the Ethical Landscape of AI in Healthcare: Insights from a Content Analysis

Yin Wu [1] and Xiang Michelle Liu [1]

[1]Affiliation not available

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Abstract

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Navigating the Ethical Landscape of AI in Healthcare: Insights from a Content Analysis

Yin Wu
School of Technology and Innovation
Marymount University
Arlington, Virginia, USA
y0w73272@marymount.edu

Xiang (Michelle) Liu
School of Technology and Innovation
Marymount University
Arlington, Virginia, USA
xliu@marymount.edu

***Abstract*— Artificial intelligence (AI) is revolutionizing healthcare, but it also poses ethical challenges that must be addressed. This study employs a content analysis approach to analyze primary policy documents and peer-reviewed articles related to ethical issues of AI in healthcare, providing insights into the ethical landscape of AI in this critical domain. While transparency and explainability are vital issues, our research highlights the need for more region-specific discussions on the ethical considerations surrounding AI in healthcare. Inclusiveness and equity of access to AI technology in healthcare must also be taken into account when designing future standards and legislation frameworks. Our findings have important implications for policymakers, healthcare professionals, and stakeholders, as they seek to navigate the complex ethical landscape of AI in healthcare. This study provides valuable insights into the critical ethical considerations surrounding AI in healthcare, and emphasizes the need for continued attention to this important issue by the broader interdisciplinary community of researchers, policymakers, ethicists, and stakeholders in the intersection of technology and society.**

***Index Terms*— artificial intelligence, content analysis, ethics, healthcare, information technology, policy**

I. INTRODUCTION

The application of Artificial Intelligence (AI) in healthcare has gained tremendous popularity over recent years, given its enormous potential for strengthening the quality and efficiency of healthcare services on a global scale. However, the deployment of AI in healthcare comes with both benefits and risks for patients, healthcare professionals, and the whole society. Ethical concerns, such as how to prevent AI from perpetuating pre-existing health disparities while incorporating its full potential in a traditional medical setting, have been pointed out by many researchers and policymakers [1, 2]. As regulatory frameworks and guidelines concerning ethical issues have been published by many organizations, there is a pressing need to present an overview of existing documents to see what has been achieved and what has yet to be emphasized in the field of AI health-related applications.

This study presents an analysis of several primary government documents and academic articles discussing ethical principles and concerns regarding the applications of AI in healthcare. To do this, computer-assistive qualitative content analysis is conducted utilizing a software program named MaxQDA. The content analysis examines principles considering several socio-ethical aspects of AI applications. Relevance among different principles and proportion of proposed practices contained under each principle is reported. This study aims to identify how each set of principles interactively influences one another and the priorities of principles that need to be addressed in future advocacy agendas.

II. BACKGROUND OF THE STUDY

There is not a single, universal definition of AI. The working definition of AI used in this study was adopted from the U.S. National Science and Technology Council (NSTC), which considers AI to be technology that "enables computers and other automated systems to perform tasks that have historically required human cognition and what are typically considered human decision-making abilities" [3]. Applications of AI in the field of healthcare have been used to perform various human capabilities, such as speech recognition, planning, and problem-solving [4]. AI technologies such as machine learning (ML) techniques are widely incorporated into medical practices to aid in the analysis of health data, decision-making, pattern recognition, and predictions. For example, an AI-enabled healthcare analytics suite is capable of predictive modeling, identifying beneficial resources, and helping patients manage costs [5]. Similar data-driven approaches have also been incorporated into a variety of applications such as wearable technologies, electronic healthcare records, and radio imaging [6]. Healthcare providers and patients are not the only entities involved in the chain of healthcare services that could benefit from the use of AI technologies. The collaboration of AI and blockchain technologies is proven to be effective in enhancing data management, access control, and integrity inside healthcare systems [7]. Aspects of healthcare services aided by this solution include but are not limited to patient data, medical supplies files, and financial information. Effective updates and management controls are thus provided to healthcare providers, patients, and other relevant specialists.

While the implementation of AI technologies has been proven to be beneficial in various ways, many medical specialists are still wary about deploying AI in diagnostic decision-making and data analysis. Concerns are also raised regarding the vulnerability of intelligent healthcare systems and the lack of stringent and universal standards for AI applications in healthcare. Moreover, other ethical issues such as biases produced unintentionally by algorithms have been found in numerous cases of AI applications. For instance, research points out that AI technologies could be biased against marginalized groups [8]. Labeling bias exists in the algorithm, causing Black patients to often be identified as not being as sick as White patients [5]. It is foreseeable that the increasing use of AI in healthcare across the globe would also be joined by ethical challenges. Therefore, many principles and guidelines have been proposed and developed by research institutions and organizations such as the World Health Organization (WHO) [6], Organization for Economic Co-operation and Development (OECD) [9], and European Commission [10]. While applications of AI, healthcare, and AI ethics are all trending topics and connectively interact with one another, oftentimes it could be hard to address discussions covering the intersection of all three fields and the interaction among them. In this research, the contents of several government and organization documents, spanning from North America to Asia, are analyzed for the purpose of discovering trends in the ethical principles of AI.

III. Methodology

The authors conducted their inquiries using a content analysis research method undergirded by an adapted grounded theory (GT) design framework. Content analysis as a research method has come into use in various fields including health studies [11, 12], organizational research [13], and management science [14]. Researchers use content analysis to identify the representation of certain words, themes, or concepts in qualitative data (e.g., texts). It is at the intersection of the qualitative and quantitative research method and particularly suitable for exploratory studies with purposes to develop a deeper understanding of a multifaceted, important, and sensitive phenomenon [15]. Through a systematic process of interpretation, the authors were able to extract structure and relationships in a large amount of textual data. This research method is chosen also because of its potential capability to help us identify problematic areas in the use of AI in healthcare and guide the process of proposing targeted policies, standards, and regulations.

A. The Grounded Theory Method Design

GT was selected as the research design framework for this study with the aim to uncover and construct insights through an iterative and recursive process of inquiry [16-18]. The GT studies generally commence with purposive sampling, followed by concurrent data collection and data analysis, and perform various stages of coding along with constant comparative analysis to lastly construct theories and insights [16, 19].

Some researchers differentiated GT from content analysis [20] as two distinctive research methods. Rather than contrasting them, we adapt the GT in this study as a research design framework, mainly to inform and guide the content analysis. In general, the content analysis consists of four stages: data collection, coding, analysis, and interpretation of coded content [14]. In the data collection stage, researchers select data sources and identify sampling criteria. In the coding phase, collected textual data are coded into different categories at various levels such as words, phrases, sentences, paragraphs, or themes. The analysis stage involves various ways and formats to present codes and relationships among different code segments. In the GT framework, the coding phase and analysis phase are intertwined to a certain extent. The authors of this study took on relational analysis that involves exploring the relationships between concepts. An evaluation of the co-occurrence of explicit concepts in the text was performed to gain insights and a big picture of the phenomenon. The interpretation stage involves the interpretation of results and drawing logical and reasonable conclusions.

B. Data Collection

One unique attribute of GT lies in its iterative and overlapping processes between data collection and data analysis [21]. To incorporate such design into the content analysis process, the authors started with initial data collection based on purposive sampling strategy. The initial search of keywords “Artificial Intelligence,” “Healthcare,” and “Ethics” from the online databases including PubMed, ProQuest, IEEE Xplore, and JSTOR returned 31,193 results. Resource types included academic articles, newspaper articles, books, reports, and even video resources. The authors also attempted several different combinations and variations of keyword synonyms and retrieved another around 40,000 results. Documents analyzed by this study are selected based on their credibility and relevance. Only peer-reviewed academic articles and reports published by governments and major intergovernmental organizations are identified as eligible sources.

After the initial screening of resource types, the number of data sources decreased to 17,945. Since one of the purposes of the study is to analyze the trend of development of AI ethical principles, all data sources have to be recent (within the past ten years) and notably address specific topics regarding ethical regulations of AI in healthcare. The specified time range further reduced the number of retrieved documents to 16,481. Then based on the content relevancy, one government document, four organization documents, and two academic articles are selected.

After further selection processes based on theoretical sampling technique [21] and selective coding, the data pool is eventually extended to ten government and organizational documents and five academic articles.

In the next step, content analysis is performed utilizing these documents as datasets. The six key ethical principles proposed by *Ethics and Governance of Artificial Intelligence for Health* by WHO ("the WHO document") are used as the basic structure of the content analysis. Under each principle, a set of sub-principles are established to accurately extract essential content from data sources. The coding function of MaxQDA is used as a major tool and code labels generated by sub-principles are input into the autocode search engine to find out occurrences of each sub-principle in different documents. Due to limitations of the autocode function, manual checks are also performed to ensure the accuracy of coded segments.

C. Coding and Data Analysis

Adapted from Strauss and Corbin's [21] model of grounded theory, multiple rounds of coding and analysis were conducted with constant comparison between the documents, the research interests, and the existing literature. As demonstrated by [22], the coding process guided by the grounded theory framework is emergent and recursive, sometimes unstructured. The essential premise is that the process guided by grounded theory is varied among different studies and subject to interpretations by different researchers [23]. Accordingly, our interpretation of primary coding segments and key coding methods have been constantly adjusted over the course of the research. Hence, to best depict the coding and analysis activities, we are reconstructing it as much as we are reporting on them.

Six ethical principles endorsed by the World Health Organization (WHO) are used as the backbone of the coding system, as shown in rectangles in Fig. 1. The principles represent major directions of AI development in existing discussions as outlined in "Ethics and Governance of Artificial Intelligence for Health" published by WHO in 2021, summarized as follows. (1) **Protect Autonomy**. AI should be designed to promote human values and enhance human dignity, rights, and freedoms. Medical decisions made in healthcare systems should remain under the full control of human beings. (2) **Promote Human Well-being, Human Safety, and Public Interest**. It is the basic requirement for any AI technologies that they should not harm people physically and mentally. AI should be designed to enhance safety, accuracy, and efficacy. (3) **Transparency, Explainability, and Intelligibility**. Transparency requires information about AI technologies to be accurate, accessible, and updated on a regular basis. AI technologies should also be explainable. Educational information should be provided to people requesting the information. Examination and evaluation should be conducted to ensure AI technologies meet the standards of safety and efficacy. (4) **Responsibility and Accountability**. The development and deployment of AI should be evaluated by patients and clinicians to ensure the responsible usage of AI. Accountability refers to responsive mechanisms when an application of AI technologies goes wrong. (5) **Inclusiveness and Equity**. AI used in healthcare should encourage equitable and appropriate access for populations regardless of race, gender, age, income, etc. (6) **Be Responsive and Sustainable**. Designers, developers, and users should continuously examine an AI technology to ensure it is responding appropriately. AI technologies should also be maintained to promote health systems and workplace sustainability.

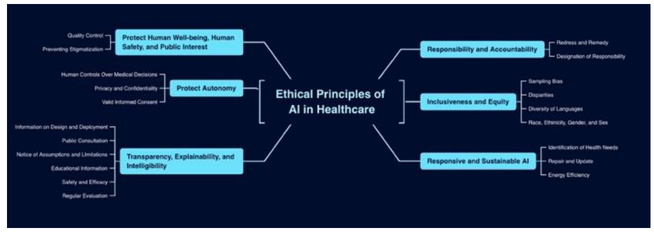

Fig. 1. Six Ethical Principles

On top of that, several sub-principles are set up for each ethical principle to describe scenarios applicable to these ethical challenges further. Each sub-principle was called a "code." All documents were then analyzed under the scope of this coding system. Respective coding labels were created for contents that were relevant to one or more code(s) through the following steps:

1. To identify eligible segments of text, a set of keywords were generated for each code. The process of generating the keywords involved consulting previous works in the field and studies utilizing a similar approach [24]. The keywords and the whole coding system can be found in the Appendix. The Autocode function of MaxQDA was then used as a search engine. After using the keywords as input sources, Autocode was able to identify segments of text containing specific keywords and label them with respective codes.

2. The Autocode function only provided a coarse screening as a first step of the coding process. It often returned repetitive or mislabeled information. For instance, a search for "race" would also return text containing "embrace" and "trace." In addition to that, polysemous words also interfered with the search results. A perfect example would be the keyword "language." Inputting "language" into the Autocode search engine would yield both results related to "human language diversity" and "natural language processing." While those two types of content could be relevant to AI ethics at the same time, they by all means should not be categorized under the same code label. Therefore, it became necessary to manually check the search results to ensure that all the keyword-containing contents were coded correctly and accurately.

3. In addition to the coding system based on ethical principles, another layer of coding mechanism was also established to further categorize the content. Eight modal verbs were used as search keywords for this

coding mechanism: shall, should, can, could, will, would, may, and might. The goal of this modal verb coding system was to differentiate between segments of documents that were calling for initiatives and those describing existing actions. While utilizing the Autocode function, the search range was limited within coded segments from Step 2. The purpose was to find out the intersections of pre-labeled coded segments in Step 2 and segments containing the modal verbs.

After the initial stage of coding, 659 coded segments belonging to 21 sub-principles were generated from the datasets. As additional documents were added to the data pool, search terms were also refined by modifying the tense and including more synonyms to better describe their parent categories. In the end, a total of 11060 coded segments were generated for the 21 sub-principles based on the coding system. The process of generating theoretical coding using a grounded theory framework involves several rounds of coding and analysis. In the first round, initial coding, data is broken down into smaller segments and each segment is given a descriptive code. These codes are then sorted and grouped together into broader categories in the next round as selective coding. This involves identifying the key themes or concepts that emerge from the data and grouping them into theoretical categories or codes. These codes are then refined and further developed through ongoing analysis and comparison with new data.

To summarize, the central categories and main codes of these rounds of analysis are illustrated in the Fig. 2. In the initial rounds of coding, we drew upon literature and generated a few codes, including "privacy", "confidentiality", "bias", and "diversity". From these categories, selective coding was conducted involving constant comparison throughout the process with literature on AI principles in healthcare through institutional and ethics lenses. The initial categories were expanded to better describe the six major ethical principles. More codes were developed for each category with the goal of more precisely extracting informative content from the article. Final rounds refined concepts with further comparison with the literature generated theoretical coding for further examination. Three theoretical conclusions were drawn to guide further analysis of data.

IV. Results and Discussion

As results, the large number of coded segments demonstrate clear patterns of appearance frequency for sub-principles. Three types of visualization methods were chosen to display the patterns: code cloud, code intersection analysis, and analysis of the modal verb system discussed above.

Code Cloud: The frequency of occurrence or the number of coded segments of each of the sub-principles is presented by the visualization tool "Code Cloud" embedded in MaxQDA. Larger sizes demonstrate higher frequencies of appearance throughout all documents. The sub-principles were colored differently based on the categories they belonged to. The frequency of occurrence has been impacted greatly throughout different stages of coding, modifications of search terms, and expansion of data pool. Fig. 3a and 3b shows the change in Code Cloud graphs from the initial stage to the final stage of coding.

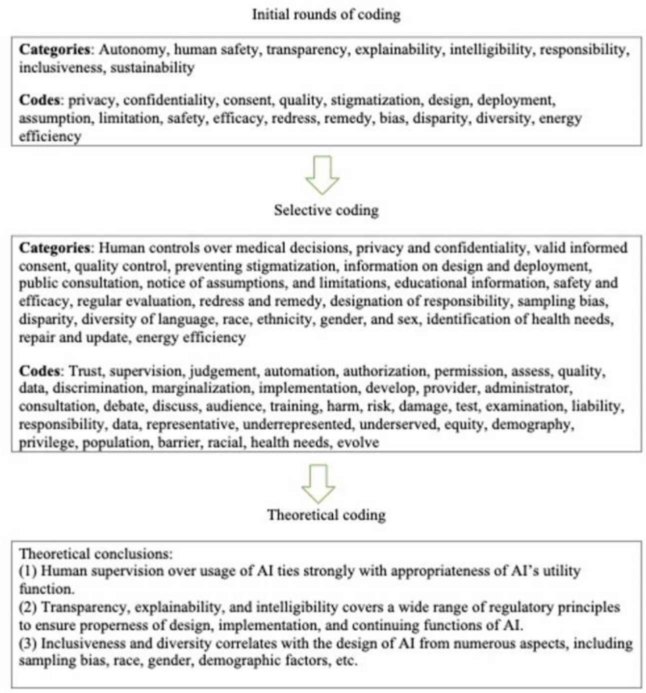

Fig. 2. Selective Coding Process

Out of all the 21 sub-principles, "Information on Design and Deployment" demonstrates the most occurrence in all documents, while "Sampling Bias" and "Quality Control" also possesses a relatively high frequency of occurrence. Design and Deployment of AI (software and medical devices) needs to comply with regulatory requirements of safety, efficacy, and accuracy and should never harm people [6]. Contents that were coded for this sub-principle primarily consist of broad statements describing AI applications in healthcare and the impacts in general. This explains why this sub-principle is the most "popular" one – possessing the highest frequency of occurrence based on the Code Map analysis. Interestingly, another sub-principle "Safety and efficacy," belonging to the same parent principle, is also displayed with a fair amount of weight on the graph. The significance underlying the design and deployment of AI is the safety of its users, and ultimately the transparency, explainability, and intelligibility of data. Sufficient information about an AI application should be published and always remain accessible to all the stakeholders involved in its design and deployment. In this way, the quality of operation and safety of users can be ensured. Thus, transparency of design and deployment of AI is the baseline of applications of intelligent healthcare systems explaining why the sub-principle is also correlated with many other code labels.

On the other hand, a significant increase in frequency of occurrence has been observed for another two sub-principles "quality control" and "sampling bias," as seen in Fig. 3b.

Fig. 3a. Code Cloud of All Documents (Initial Coding)

Fig. 3b. Code Cloud of All Documents (Final Results)

Code Intersection Analysis: The code model function of MaxQDA is used to analyze the frequency of co-occurrences of different sub-principles. Co-occurrence, or intersection, of two sub-principles in the MaxQDA code model, stands for times when two coded segments belonging to different sub-principles overlap or partially overlap with one another. While not all sub-principles demonstrate strong co-occurrence behavior, Fig. 4 grasps a significant portion of the intersection analysis to best display code labels with strong intersections and are meaningful for further analysis.

Despite code labels under the same principles demonstrating strong proximity as expected, sub-principles belonging to different principles also occur in the same or close sections of documents frequently. For instance, "Preventing Stigmatization" displays strong proximity to "Disparities", as long as "Race, Sex and Ethnicity". While the latter two are categorized under the general principle "Inclusiveness and Equity," it is interesting yet not surprising to see the core codes connect and echo with the principle of "Human Safety and Public Interest," the parent principle of "Stigmatization." Inclusiveness is the key requirement for AI healthcare applications to ensure equal, appropriate, and non-discriminatory access to whichever services they provide. This further suggests that ensuring inclusivity and equity in AI healthcare applications is not only important in its own right, but is also closely linked to ensuring the safety and well-being of users. By addressing disparities and preventing stigmatization based on factors such as race, sex, and ethnicity, AI healthcare applications can promote greater access and equity while also promoting the safety and well-being of all users. Overall, this analysis highlights the importance of considering these two principles together and ensuring that AI healthcare applications are designed and implemented in a way that prioritizes both inclusivity and safety.

Another pair demonstrating a great amount of intersection is "Regular Evaluation" and "Public Consultation". Despite being categorized as different sub-principles, the codes "Regular Evaluation" and "Public Consultation" demonstrate a significant overlap in the policy documents. While regular evaluation is essential for monitoring and assessing AI systems' performance and impact, public consultation emphasizes engaging with a diverse range of stakeholders, including patients and caregivers, in the development and deployment of AI in healthcare. The intersection between these two codes underscores the importance of transparency, accountability, and stakeholder participation in ensuring the responsible and ethical development of AI in healthcare. This highlights the need for a collaborative and participatory approach to AI ethics, where stakeholders' input is valued and taken into account throughout the development and deployment process. By engaging stakeholders and ensuring transparency and accountability, we can develop AI systems in healthcare that are responsive to the needs and concerns of the communities they serve. Prioritizing these principles can allow us to work towards building a more just, equitable, and effective healthcare system that leverages the power of AI to improve health outcomes for all.

Fig. 4. Code **Model** of Intersection Analysis

Modal Verb Analysis: As described in the Coding section, a set of modal verbs is utilized to differentiate coded segments that are proposing legislations, frameworks, and future practices from the rest. Fig. 5 shows the percentages of coded segments labeled by the modal verb search under each principle. The principle of "Human Safety and Public Interest" has the highest proportion of proposed practices (66.67%) while the percentage of "Inclusiveness and Equity" is the lowest of all six principles (48.54%). Overall, there is no significant difference between any two principles with all the percentages staying within the range between 40% and 60%.

In the comparison of modal word labeling and ethical principles, Inclusiveness and Equity possess the lowest percentage of content related to proposed practices – 48.56%. In this study, inclusiveness and equity include biases in the data sampling process, disparities, and diversity in languages, race, and gender. Ideally, equitable access to the benefits of AI applications in healthcare should be ensured regardless of race, gender, and other socio-economic factors. The sub-principles Sampling Bias and Race, Sex, and Ethnicity display a noticeable level of frequency in the Code Cloud analysis, meaning that such challenges are identified across the datasets and there are a certain number of discussions involving the inclusiveness and equity of access to AI technology. However, the trend of calling for future standards and practices remains relatively low compared to other principles. A great number of discussions revolve around ethical challenges in technical aspects with focuses on sampling bias within training data of AI and lack of demographic representation in data collection [25]. Proposals regarding such ethical issues point more toward categories such as Design and Deployment of AI, leaving a gap between the growing inequalities of technology resources distribution and actual attention granted toward resource-scarce regions and populations. In addition to that, data collection and relevant research are also limited in regions suffering from insufficient accessibility to technology, making it hard for AI developers and regulators to bring up discussions and future proposals targeting the specific challenges these regions face.

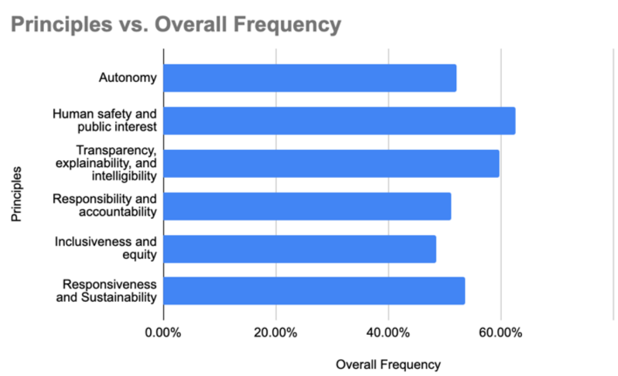

Fig.5. Overall Percentage of Proposed Practices in Each Principle

Three Themes

By using a grounded theory framework to analyze policy documents on AI ethics in healthcare, the study was able to generate theoretical coding that provides insight into the key ethical considerations surrounding the development and deployment of AI in healthcare.

In conclusion, our content analysis of various policy documents on artificial intelligence ethics in healthcare reveals several important findings. Firstly, the role of designers, developers, and administrators in the design of AI systems is a crucial consideration that should be given priority. Without their active involvement in the development process, ethical considerations may be overlooked, resulting in unintended consequences that could potentially harm patients.

Secondly, our analysis highlights the importance of inclusiveness and equity in the development and deployment of AI in healthcare. These principles are not only essential for ensuring that the benefits of AI are accessible to all, but they also interact with other ethical considerations, such as privacy and autonomy.

Finally, we note that there is a relative insufficiency in the current discussion regarding sustainability and energy efficiency in the development and deployment of AI in healthcare. While these principles may not be as frequently mentioned as others, they are nonetheless important considerations that should be addressed to ensure that the long-term impact of AI on the environment is minimal.

Overall, our analysis suggests that while there is a growing awareness of the ethical considerations surrounding AI in healthcare, there are still areas that require further attention and discussion. By actively engaging with these issues, policymakers, developers, and administrators can ensure that AI is developed and deployed in a way that is ethical, equitable, and sustainable.

V. Limitations

By extending the data pool to a global scale, the study was able to build a data pool resulting in more than ten thousands of coded segments for analysis. However, it has also been noticed in the literature search process that discussions spanning all three fields of AI technology, healthcare, and ethical regulations could be hard to find. Thus, the study had to incorporate numerous documents that only addressed two out of the three topics. Unintentional biases have been imposed as a result. For instance, healthcare related search terms such as “Human Control Over Medical Decisions” would not be reflected as much in documents that only discussed general AI applications. The methodology of constructing the coding system also contains some limitations. The search terms are generated with references to relevant works while also incorporating ideas from web databases and expertise from the field. The lack of a rigid standard might lead to the inability to capture complete context and information. The structure of code labels also limits the capabilities of differentiating between the frequency and relevance of coded segments. For instance, a keyword that appears in a topic sentence might not imply the same significance as its appearance in a description of a real-world incident.

VI. Conclusions

The findings of this study provide valuable insights into the ethical considerations surrounding the development and deployment of artificial intelligence in healthcare. The three key themes that emerged from our analysis - "Information on Design of AI", "Inclusiveness and Equity", and "Insufficiency in current discussion in other aspects such as sustainability and energy efficiency" - highlight the need for a more comprehensive approach to AI ethics in healthcare.

Of particular significance is the theme of "Information on Design of AI", which emphasizes the critical role of designers, developers, and administrators in ensuring that ethical considerations are incorporated into the development process of AI systems in healthcare. This theme highlights a novel and relevant perspective on the ethical implications of AI in healthcare and underscores the importance of including a diverse range of stakeholders in the development and deployment of AI systems.

AI technologies have been rapidly integrated into many forms of medical practices and many regulatory frameworks have been proposed to ensure the safe implementation of AI applications. However, challenges remain as to how such regulations should be standardized and further developed to meet universally agreed requirements of AI safety in healthcare. One of the urgencies of maintaining safe integration of AI healthcare applications is for AI-targeted user groups to receive proper training and educational information about AI technologies. Priorities of educational information that should be included in AI training are outlined by white papers for medical specialists, including terminology, statistics, and ethics of AI applications. Many UK universities have developed educational curricula related to AI applications for healthcare to meet the demands of the medical specialist community to be equipped with the necessary skills and knowledge for the future of AI-enabled healthcare [26]. Integrating AI training into post-secondary education might serve as an effective measure of preparing the health workforce to meet the safety standards of AI implementation and should be promoted on a global scale. On the other hand, surveys revealed that the knowledge and preparedness of medical practitioners currently in the field of AI technologies remained generally low [27]. Training and educational programs for AI need to be established as a supplement to the post-secondary component as the current healthcare workforce also demands educational information to overcome the weakness of limited AI knowledge. Meanwhile, it is critical for any types of educational programs to be kept updated and served to their target groups regularly. Maintaining the transparency and explainability of AI technologies is the primary goal of promoting educational curricula and is also among the fundamental principles of ethics of AI in healthcare.

The theme of "Inclusiveness and Equity" emphasizes the need for AI in healthcare to be accessible to all, regardless of their background or socioeconomic status. Inclusiveness and equity of AI applications in healthcare should also be taken as a priority when proposing future regulatory frameworks in the field. While AI is known to be susceptible to biases in algorithm design and data sampling, such biases will only be amplified and exacerbated in any future public health emergency as has already been seen during the Covid-19 pandemic. The unintended biases embedded in the design of AI should be carefully considered when generating regulations on the design and implementation of AI applications in healthcare. Inequalities and injustices brought in by labeling discrimination would also make an impact on decisions generated by AI algorithms, thus highlighting the importance of human oversights over any AI-integrated decision-making process and underscoring the relevance of AI ethics in broader societal debates around equity and fairness.

The third theme highlights the novelty and relevance of the study by identifying areas that require further attention and research, such as sustainability and energy efficiency, and by pointing to the need for ongoing engagement with stakeholders in order to ensure that ethical considerations are fully addressed.

While the six fundamental principles serve as the basic requirements of AI applications in healthcare in terms of protecting data safety and respecting human rights, specific challenges are imposed for the real-world implementation of regulatory frameworks. This study intends to provide insight into the current ongoing discussion of ethical principles of AI technologies. However, how successfully applying these concepts into minimizing the risks of AI technologies would cost top-down efforts engaging various aspects of healthcare fields. More work remains to be done by regulators and administrative bodies to articulate region-specific solutions derived from discussions on a global scale.

APPENDIX

TABLE I
Coding System and Keyword Inputs for Autocode

Principles	Sub-principles	*Keywords*
Protect autonomy	Human Controls Over Medical Decisions	*Human control* *Medical decisions* *Trust, supervision* *Judgment* *Automation bias*
	Privacy and confidentiality	*Privacy* *Confidentiality* *Authorized*
	Valid informed consent	*Consent* *Inform* *Permission*
Protect human well-being, human safety, and public interest	Quality control	*Assess* *Quality* *Data*
	Preventing stigmatization	*Stigmatization* *Discrimination, discriminatory* *Marginalization*
	Information on design and deployment	*Information* *Design* *Implementation* *Deployment, develop, developer* *Provider, administrator*
		Consultation

Transparency, explainability, and intelligibility	Public consultation	*Debate* *Discuss*
	Notice of assumptions and limitations	*Assumption* *Limitation*
	Educational information	*Education* *Audience* *Training*
	Safety and efficacy	*Safe, safety* *Efficacy* *Harm* *Risk* *Damage*
	Regular evaluation	*Evaluation, evaluate* *Test* *Examination*
Responsibility and accountability	Redress and remedy	*Redress* *Remedy*
	Designation of responsibility	*Liability* *Responsibility, responsible*
Inclusiveness and equity	Sampling bias	*Data* *Sample* *Bias* *Representative*
	Disparities	*Underrepresented* *Underserved* *Equality, equity, equitable* *Demographic* *Priviledge* *Population*
		Language
	Diversity of languages	*Barrier*
	Race, ethnicity, gender, and sex	*Race, racial, racism* *Ethinicity, Ethnical* *Gender* *Sex*
Responsive and sustainable AI	Identification of health needs	*Health needs*
	Repair and update	*Repair* *Update* *Evolve*
	Energy efficiency	*Energy* *Efficiency*

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