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Ethical frameworks and predictors of ethical artificial intelligence adoption in Kenya's health sector

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A B S T R A C T

This study used a mixed-methods approach that combined a semi-structured questionnaire with a systematic literature review to examine the factors that influence ethical Artificial Intelligence (AI) adoption in Kenya's health sector. The aim was to provide evidence to support both policy development and practical implementation. Data were collected from 150 healthcare providers working in healthcare institutions and digital health companies in Kenya and were analyzed using multiple linear regression. The main independent variables were data governance, ethical awareness, regulatory compliance, and organizational accountability. The results showed that all four variables significantly predicted ethical AI adoption. Data governance ($\beta = 0.3157$, $p < .05$) and ethical awareness ($\beta = 0.2415$, $p < .05$) were the strongest predictors, followed by organizational accountability ($\beta = 0.1894$, $p < .05$) and regulatory compliance ($\beta = 0.1128$, $p < .05$). Diagnostic tests confirmed the validity of the regression model (VIF < 3.0, Durbin–Watson = 2.12, $p > .05$). The findings highlight the importance of strengthening data governance practices, developing human capacity, improving organizational accountability, and ensuring compliance with existing regulatory frameworks to support faster and more ethical AI adoption in the healthcare sector. The paper concludes with policy recommendations that emphasize Afrocentric ethical perspectives inspired by African philosophies such as Ubuntu, capacity building for stakeholders in the healthcare ecosystem on ethical AI, stronger regulatory systems, and efforts to increase public trust in AI-based healthcare solutions.

1. Introduction

Healthcare systems worldwide are being impacted by Artificial Intelligence (AI), which is making significant progress in areas such as predictive diagnosis, patient data management, and telemedicine. Kenya's health sector has seen an increase in the use of AI technologies, particularly in diagnosing and predicting epidemics as well as managing digital health. However, despite the potential advantages of these technologies, their ethical implications remain poorly understood, especially in resource-constrained countries such as Kenya. Kerasidou (2021) identified data privacy, algorithmic bias, the lack of explainability of AI models, and patient autonomy as major concerns in the adoption of AI in the health sector. If these concerns are not addressed, the Kenyan health sector risks losing out on potential AI opportunities. Other critical sectors also likely not to realize AI potential unless these issues are taken care of include finance, education, and agriculture, which remain critical drivers of the economies of several African countries.

With the Digital Economy Blueprint and the Data Protection Act highlighting Kenya's commitment to digital transformation, it has become increasingly clear that an effective ethical framework is necessary for AI adoption in the Kenyan health sector. The AI governance in Kenya is still developing, fragmented, and heavily reliant on outside tech industries, a scenario replicated in several African countries. This raises key questions: Is the Kenyan health sector ready for the adoption of AI technologies? What key challenges must be addressed for the successful ethical adoption of AI technologies in the Kenyan Health Sector? What organizational and systemic barriers must be addressed as prerequisites for implementing AI in the healthcare industry? What

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are the most effective policy changes required for implementing ethical AI in healthcare in Kenya? By investigating the connection between institutional ethics capacity and ethical AI adoption in Kenya's healthcare context, this study aimed to empirically investigate these questions. Using a multiple linear regression model and a mixed-methods approach, the study provides empirical support for the largely theoretical discussion of AI ethics in Africa. With an emphasis on the Kenyan healthcare system as a crucial example of digital transformation in the Global South, this study offers a data-driven understanding of the predictors of ethical AI adoption.

A paradigm shift that could completely rethink healthcare delivery is represented by the quick adoption of artificial intelligence (AI) in Kenya's healthcare system. Innovative solutions like IBM's Watson for Oncology pilot projects, Baobab Health's diagnostic tools, and the mobile health platform m-TIBA are examples of the growing trend toward AI-driven solutions that aim to improve diagnostic accuracy, optimize resource allocation, and facilitate data-driven clinical decision-making. Nonetheless, the rapid advancement of technology is surpassing the establishment of a commensurate ethical and regulatory framework, resulting in a crucial governance void. As a result, the implementation of these systems has brought forth several intricate moral conundrums that pose a threat to public confidence and fair health outcomes. Persistent issues include unclear data ownership rights, the "black box" nature of many machine learning models that obscure their reasoning, the integrity of informed consent processes when decisions are based on opaque algorithms, and a significant lack of clarity regarding accountability when automated systems make mistakes. In a resource-constrained environment like Kenya, where digital literacy may vary, and regulatory enforcement is still developing, these difficulties are especially severe.

Although the creation of the Office of the Data Protection Commissioner (ODPC) and the passage of the Data Protection Act in 2019 represent important advancements, their frameworks are largely generic and not especially designed to address the particular risks that artificial intelligence poses in delicate fields like healthcare. Most hospitals and health tech startups are therefore ill-equipped to mitigate algorithmic bias, ensure explainability, or uphold ethical standards in automated care pathways because they lack strong, AI-specific governance mechanisms. This implementation gap is reflected in the scholarly discourse. Most of the Kenyan academic research on AI ethics is conceptual in nature or concentrates on high-level policy analysis (Onyango, 2021; Juma and Faturoti, 2025). The empirical, industry-specific research that examines the practical realities of AI implementation in clinics and hospitals is lacking. Importantly, no previous study has used a quantitative methodology to systematically identify and evaluate the pertinent predictors that affect the adoption of ethical AI practices in the Kenyan health sector, including institutional readiness, regulatory perceptions, and ethical awareness. As a result, healthcare administrators and legislators lack an evidence-based plan to direct their interventions on AI adoption and utilization in the healthcare sector. The theoretical foundations of AI ethics and their practical application within Kenya's health ecosystem remain markedly misaligned. To address this disparity, this study moved beyond conceptual discourse and undertook a rigorous empirical investigation. Specifically, the study developed and tested a multiple linear regression model designed to link core ethical constructs with measurable institutional, regulatory, and organizational indicators. This analytical approach enabled the generation of evidence-based recommendations to guide the ethical and equitable adoption of AI in Kenya's healthcare sector. The robustness of the findings was further reinforced through an extensive review of state-of-the-art literature.

The general objective was to examine the predictors of ethical AI adoption in Kenya's health sector.

The study was guided by the following four specific objectives:

1. To assess the influence of ethical awareness on ethical AI adoption in the Kenyan Health Sector
2. To assess the influence of data governance on ethical AI adoption in the Kenyan Health Sector
3. To assess the influence of regulatory compliance on ethical AI adoption in the Kenyan Health Sector
4. To assess the influence of organizational accountability on ethical AI adoption in the Kenyan Health Sector

The study sought to test the following four null hypotheses.

H_{01}: Ethical awareness has no statistically significant influence on the adoption of ethical AI in the Kenyan health sector.
H_{02}: Data governance has no statistically significant influence on the adoption of ethical AI in the Kenyan health sector.
H_{03}: Regulatory compliance has no statistically significant influence on the adoption of ethical AI in the Kenyan health sector.
H_{04}: Organizational accountability has no statistically significant influence on the adoption of ethical AI in the Kenyan health sector.

2. Literature review

2.1. Theoretical framework

An integrated, multi-level theoretical framework that combined the Theory of Planned Behavior, the Technology-Organization-Environment (TOE) Framework, and Institutional Theory served as the foundation for this investigation. A thorough examination of the ethical adoption of AI in healthcare was made possible by this tripartite foundation, which covered institutional pressures at the macro level, organizational contexts at the meso level, and individual behaviors at the micro level. The main justification for why healthcare organizations feel pressured to implement moral AI practices is found in Institutional Theory (DiMaggio and Powell, 1983). According to this theory, organizations seek legitimacy by submitting to three isomorphic forces that appear in their institutional environment. First, the concept of Regulatory Compliance (RC), which requires adherence to the Data Protection Act and ODPC guidelines, is directly informed by coercive isomorphism, or the formal pressure from laws and regulations. Second, the construction of Ethical Awareness (EA), which represents healthcare professionals' comprehension of AI ethics principles, embodies normative isomorphism that originates from professional standards and education (Floridi et al., 2018). Finally, the adoption of established Data Governance (DG) mechanisms and Organizational Accountability (OA) structures, such as ethical review boards and audit procedures, to lower risk and improve legitimacy, is an example of mimetic isomorphism, which happens in response to uncertainty and drives organizations to emulate successful peers (Kerasidou, 2021).

The Technology-Organization-Environment (TOE) Framework (Tornatzky et al., 1990) provides a meso-level structure to classify the contexts in which these constructs operate, while Institutional Theory explains the "why" behind the adoption pressures. Data Governance (DG), which guarantees data quality, integrity, and security, addresses the technological context, which is characterized by AI systems and their intrinsic requirement for high-quality data. Ethical Awareness (EA) and Organizational Accountability (OA), which stand for the formal structures and human capital required for ethical implementation, shape the organizational context, which includes the firm's internal features and resources. Lastly, the Regulatory Compliance (RC) requirements that shape the legal and competitive landscape have a significant impact on the environmental context, or the arena in which the organization operates. The Theory of Planned Behavior (TPB) (Ajzen, 1991) functions at the micro level to explain the psychological process by which these more general factors impact the intention of a healthcare professional to use AI ethically, completing the multi-level analysis. Three factors determine behavioral intention, according to TPB. The Ethical Awareness (EA) construct captures the foundational knowledge that shapes an individual's attitude toward the behavior. The external Regulatory Compliance (RC) environment and the internal expectations enforced by Organizational Accountability (OA) create subjective norms, or perceived social pressure. Finally, OA structures that offer clear channels of support and reporting, as well as strong Data Governance (DG) protocols that streamline proper data handling, support perceived behavioral control, or the ease with which one can act ethically.

In conclusion, the Technology-Organization-Environment (TOE) Framework, the Theory of Planned Behavior (TPB), and Institutional Theory were combined in this study's integrated theoretical framework to investigate the ethical implementation of AI in healthcare at the macro, meso, and micro levels. Through normative (Ethical Awareness), mimetic (Data Governance and Organizational Accountability), and coercive (Regulatory Compliance) isomorphisms, institutional theory explains organizational pressures to adopt ethical AI. These concepts are contextualized by the TOE framework, where the environmental context is captured by regulatory compliance, the organizational context is defined by organizational accountability and ethical awareness, and the technological context is represented by data governance. TPB describes how these elements influence people's intentions to use AI ethically on a micro level. Ethical awareness shapes attitudes, organizational accountability and regulatory compliance create arbitrary standards, and data governance and organizational accountability increase the perception of behavioral control. When combined, these theories provide a thorough understanding of the organizational, institutional, and personal predictors that influence the ethical adoption of AI in healthcare.

2.2. Global ethical frameworks for AI in healthcare

A set of well-established, high-level principles is increasingly serving as the global guide for the ethical application of AI in healthcare. The discourse is anchored in the fundamental bioethical pillars of beneficence, non-maleficence, autonomy, and justice by foundational documents like the AI4People framework (Floridi et al., 2018). The OECD (2019) and the WHO (2024) both place a strong emphasis on inclusivity, explainability, and a human-centered approach, while the European Commission's Ethics Guidelines for Trustworthy AI in 2019 call for human agency and oversight, technical robustness, and transparency. Together, these frameworks provide a strong, consensus-driven foundation for assessing and directing the global application of ethical AI, serving as an essential springboard for any national policy debate. However, the geopolitical and sociocultural origins of these powerful frameworks present a significant challenge. They are primarily conceptualized within the institutional frameworks of the Global North and are subtly influenced by presumptions of strong data infrastructure, developed regulatory capabilities, and liberal-individualist social contracts. There may be a substantial "ethics-implementation gap" when these models are directly applied to the realities of African health systems, which are frequently marked by resource limitations, infrastructure fragmentation, and divergent philosophical tenets. This is a serious philosophical and cultural misalignment rather than just a practical issue.

The fundamental principle of individual autonomy and consent serves as a striking example of this dissonance. The importance of the individual data subject is the foundation of laws such as the General Data Protection Regulation (GDPR) of the EU, which has a significant influence on Kenya's Data Protection Act. On the other hand, personhood and decision-making are frequently situated within a network of familial and community relationships in African communalist philosophies, particularly the Ubuntu ethic of "I am because we are" (Yilma, 2025). Therefore, a stringent GDPR-style requirement for individual informed consent for the use of health data may be incompatible with cultural customs in which elders in the family or community play a crucial role in healthcare decisions. This leads to a real-world conundrum where rigorous adherence to a global standard might unintentionally disregard regional social norms, potentially undermining the very trust that ethical frameworks are intended to foster. Thus, although global principles offer a crucial vocabulary, their blind acceptance runs the risk of resulting in a kind of "ethical colonialism," in which norms established by outside parties impede the creation of contextually relevant and long-lasting governance models for AI in Kenya's healthcare system.

2.3. AI ethics in African contexts

With the adoption of artificial intelligence accelerating at an astounding rate across critical sectors like healthcare, financial services, and agriculture, the African continent is currently undergoing a digital transformation. However, this surge is taking place against a backdrop of largely undeveloped and disjointed regulatory frameworks. The creation of customized, legally binding AI policies in most member states is still in its infancy, despite the acknowledged urgency of regulating the digital ecosystem. Because of this regulatory lag, there is a risk that technological advancement will surpass the safeguards required to guarantee that it benefits the public, creating a dangerous environment. A growing number of academics and influential people are calling for a paradigm change away from imported models to address this governance gap. They assert that having a true Afrocentric ethical viewpoint is not only better but also necessary. According to this viewpoint, AI governance must be rethought from a perspective that prioritizes restorative social justice over merely technical fairness, intergenerational solidarity over short-term profit, and communal well-being over radical individualism. This critical contextualization, which maintains that ethical frameworks are based on the lived realities and value systems of the societies they are intended to serve, is not a rejection of global principles.

The healthcare industry has the highest stakes in this debate regarding ethical AI adoption. In this case, moral dilemmas are very real and human rather than abstract. There is a serious risk of data exploitation, whereby biodata from African populations, a useful resource for developing diagnostic algorithms, could be taken without providing fair local benefits, thus sustaining a kind of digital colonialism. Furthermore, AI-powered health tools run the risk of exclusively benefiting urban elites due to the widening gap in digital inequality, which would exacerbate already-existing health disparities between the rich and the poor, the connected and the isolated. The threat of "algorithmic dependency," which would undermine national health sovereignty and local capacity building by making health systems permanently dependent on foreign technology providers' advanced AI platforms, is perhaps the most pernicious. In this continental framework, South Africa, Nigeria, and Kenya have become leading centers of AI innovation in Sub-Saharan Africa. However, there is a crucial paradox in their leadership. Instead of being naturally co-created from local ethical norms and grassroots consultation, their policy frameworks frequently remain derivative, heavily adapted from Western templates like the GDPR, despite being at the forefront of technological experimentation (Juma and Faturoti, 2025). A fundamental misalignment results from this policy mimicry. The significant linguistic diversity of the continent is usually not taken into consideration by AI systems controlled by these ill-suited frameworks, which frequently leave out regional languages and dialects. The glaring socioeconomic gaps that dictate who has access to and confidence in digital health tools are too great for them to handle. Furthermore, by creating a fictitious, tech-savvy user that does not accurately reflect the typical citizen or healthcare professional, they ignore the crucial issue of low digital literacy. The result is a systemic failure rather than merely a technical one, which is the application of AI that is socioeconomically exclusive, culturally tone-deaf, and ultimately unsustainable in attaining fair health outcomes for the African populace.

2.4. The Kenyan health sector and AI adoption

Kenya has established itself as a leader in the use of AI in healthcare, implementing a variety of strategies meant to overcome structural obstacles and enhance patient outcomes. These projects demonstrate a range of uses, from sophisticated clinical decision-support to administrative efficiency. For example, the m-TIBA platform serves as more than just a mobile health wallet; it has established a dynamic health ecosystem that aims to provide resources to low-income populations, aggregates large datasets on treatment patterns, and enables conditional payments. IBM Watson for Oncology, a breakthrough in clinical AI, was tested at the Aga Khan University Hospital. It provided data-driven treatment recommendations for cancer care, marking a major advancement in personalized medicine (Kerasidou, 2021). To anticipate infection hotspots and maximize the distribution of limited resources, such as intensive care unit beds and testing kits, the Ministry of Health used predictive modeling systems during the COVID-19 pandemic. In addition, organizations such as Kenya Medical Research Institute have implemented AI-powered chatbots that attempt to bridge a significant gap in the delivery of mental health services by offering scalable mental health counseling, conducting initial triage, and providing essential psychosocial support. Privacy and data sovereignty are important issues. Sensitive patient data is frequently stored on commercial cloud servers outside of Kenya, putting it under foreign jurisdiction and exposing it to risks that Kenyan regulators cannot directly control. This is the case with platforms such as m-TIBA. This leads to a conflict between national control over vital health data and technological efficiency. These advancements serve as a live example of the serious ethical issues that arise when technology surpasses governance, even as they highlight Kenya's enormous technological potential and adaptability.

Furthermore, in practice, the fundamental ethical precept of informed consent is frequently minimized. Consent is usually obtained through a digital "click-through" agreement, which may not be a true understanding or voluntary agreement, particularly when people are in vulnerable health situations or have low levels of digital literacy. The widespread and mostly ignored risk of algorithmic bias exacerbates this. Clinical and genomic data from non-African populations are frequently used to train the machine learning models that support diagnostic tools and predictive systems. When applied to Kenyan patients, this can result in a risky lack of efficacy and accuracy, possibly misdiagnosing conditions or suggesting less-than-ideal treatments (Juma and Faturoti, 2025).

Due to the "black-box" nature of these intricate algorithms, this bias is frequently unknown and unchecked, causing medical professionals to rely on advice they are unable to confirm (Floridi et al., 2018). As a result, these technologies, despite their potential for efficiency, present new avenues for inequality and risk, functioning within a regulatory environment that lacks the specialized knowledge and legal frameworks necessary to guarantee their efficacy and morality.

2.5. Conceptual framework

Four key concepts emerged from the review of the literature, and they serve as the crucial predictors that determine whether ethical AI is successfully implemented in developing nations. The first is Ethical Awareness (EA), which measures how well healthcare workers comprehend the fundamentals of AI ethics and their responsibilities to protect patient data (Floridi et al., 2018). Throughout its lifecycle, data quality, integrity, and security are guaranteed by institutional mechanisms like policies and protocols, which are included in the second construct, Data Governance (DG). The need to align AI systems and their use with sectoral and legal frameworks, such as the Data Protection Act and Office of the Data Protection Commissioner guidelines, is the third determinant, or Regulatory Compliance (RC). Lastly, Organizational Accountability (OA) highlights the significance of formal internal structures to enforce and monitor ethical practices, including internal codes of conduct, regular audit procedures, and ethical review boards (Kerasidou, 2021). These four constructs collectively served as the fundamental framework for the empirical model that was examined in this study. The four predictors of ethical AI adoption are indicated in Fig. 1.

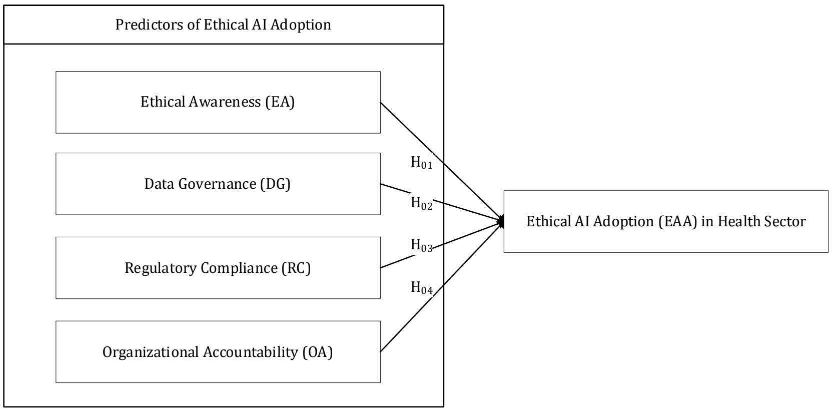

Fig. 1: Conceptual framework

3. Methodology

3.1. Research design

A mixed-methods research design that combined qualitative and quantitative techniques was used in this study. A cross-sectional survey of Kenyan health professionals comprised the quantitative component, while a review of the literature and qualitative data from the semi-structured questionnaire comprised the qualitative component. The deployment of a mixed-methods research design improved the validity of findings by facilitating triangulation between theoretical constructs and empirical evidence (Creswell and Creswell, 2018). The chosen design further allowed the capturing of both measurable relationships and contextual insights that cannot be quantified through numerical responses alone (Creswell and Creswell, 2018). The goal of the study was to measure the impact of institutional ethics capacity on the adoption of ethical AI in the healthcare sector in Kenya. Ethical Awareness (EA), Data Governance (DG), Regulatory Compliance (RC), and Organizational Accountability (OA) were the independent variables, and Ethical AI Adoption (EAA) was the dependent variable. Quantitative data were collected using closed-ended, Likert-scale items, while qualitative data were obtained through open-ended questions and subsequently analyzed using thematic analysis. Table 1 presents the key study variables, including their operational definitions and the specific indicators incorporated in the questionnaire to facilitate the collection of both quantitative and qualitative data.

Table 1: Operational definition of constructs

Construct	Type of variable	Operational definition	Likert questions' indicators	Qualitative questions' indicators
Ethical AI adoption (EAA)	Dependent	The degree to which AI is implemented ethically, including considerations based on fairness, transparency, autonomy, and human oversight	Ethical AI tools Accuracy and bias testing Staff training Rights-preserving AI use Human review of AI outputs Equitable benefits for all groups	AI system example with ethics Improving ethical AI adoption Concerns about long-term AI reliance.
Ethical awareness (EA)	Independent	The level of understanding of AI concepts, ethical principles, risks, and implications of AI in the healthcare sector in Kenya	Understanding of AI systems Awareness of algorithmic bias Understanding black-box issues Training in AI ethics Identification of ethical risks Awareness of Ubuntu ethics	Ethical risks of AI Needed ethics training Integration of Afrocentric ethics
Data governance (DG)	Independent	Policies and practices for ensuring data quality, accuracy, security, access control, and ethical handling	Existence of governance policies Data quality checks Secure storage Data governance officer Data-sharing protocols Data sovereignty awareness	Data governance challenges Strengthening data governance Data sovereignty considerations
Regulatory compliance (RC)	Independent	Understanding and adherence to Kenya's Data Protection Act, ODPC requirements, and AI regulations	Familiarity with DPA 2019 Institutional compliance Consent clarity DPIAs conducted Compliance audits Awareness of non-compliance penalties	Regulatory gaps Areas needing strengthening Needed regulatory institutions
Organizational accountability (OA)	Independent	Establishment of ethics committees, reporting structures, audits, and cultural norms ensuring ethical AI adoption and use	Ethics committees exist Clear accountability lines Leadership transparency Safe reporting channels Monitoring of AI systems Human-centered organizational values	Organizational accountability Needed oversight structures Building community trust

3.2. Study area and population

An extensive public system, a rapidly growing private sector, and a trailblazing ecosystem of health technology startups interact intricately in Kenya's dynamic and multi-layered health sector, which is the setting in which this study was carried out. A meticulously designed sampling framework was used to guarantee that the study included a thorough and representative cross-section of technological adoption environments. To facilitate comparative analysis, the study population was methodically selected from three different strata. Public healthcare facilities, including carefully chosen county referral facilities and national referral hospitals, made up the first stratum. These facilities are examples of high-volume, intricate care settings that function inside formalized legal, regulatory, and procurement frameworks. Leading private hospitals and healthcare networks, which generally exhibit greater operational and financial flexibility in their adoption of technology, were included in the second stratum. This provided insights into the dynamics of market-driven implementation. Digital health startups and innovation hubs like m-TIBA and Access Afya, which are the most technologically advanced in the industry and are essential for comprehending new ethical paradigms, were included in the third stratum.

Key informants who were directly involved in the lifecycle of health technologies made up the target population, guaranteeing that data collection included a variety of professional viewpoints. These included medical administrators and policymakers who have an impact on strategic procurement and governance decisions; ICT and health informatics officers who are in charge of technical implementation and system maintenance; clinical professionals like physicians and nurses who use AI systems for diagnosis and treatment as end users; and specialized data governance managers who are in charge of making sure that ethical data management and regulatory compliance are followed. The purpose of this multi-stakeholder approach was to intentionally triangulate viewpoints from healthcare organizations' technical, strategic, and operational levels.

3.3. Sample size and sampling procedure

The study employed a mixed-mode sampling, attempting to achieve a compromise between statistical representativeness and pragmatic issues of fieldwork. For the main methodology, stratified sampling was used to enable proportional representation from each of the three pre-identified institutional categories (public hospitals 60%, private organizations 25%, and digital health startups 15%). The allocation reflects the current distribution of specialized healthcare service delivery and advanced technological capability in Kenya's health sector. The final sample consisted of 150 individuals, which was considered statistically sound for the planned multiple linear regression model. This determination followed established methodological guidelines from Hair et al. (2019), which recommend a minimum ratio of 5 to 20 observations per independent variable to ensure reliable parameter estimates and sufficient statistical power. By incorporating four primary predictor variables into the core regression model, the sample size of 150 participants resulted in a 37.5 observations per variable rate, exceeding its conservative limit, and effectively reducing the risks of model overfitting. A two-stage sampling strategy was employed within each institution to ensure that the data collected were both relevant and of high quality. First, institutions were selected using proportional stratified sampling. Thereafter, purposive sampling was applied to identify individual respondents who met the inclusion criterion of having direct professional engagement with health technologies or data systems. Purposive sampling is particularly suitable for research involving highly specialized domains such as AI governance, where general staff may lack adequate exposure or expertise (Hair et al., 2019). By integrating institutional stratification with the deliberate selection of knowledgeable participants, this methodological design ensured that the dataset was both demographically representative and rich in practical insights. Consequently, the approach enhanced the validity and generalizability of the study's findings across Kenya's healthcare ecosystem.

3.4. Data collection instrument

A semi-structured questionnaire integrating closed-ended Likert-scale items with open-ended questions to facilitate a comprehensive understanding of institutional, regulatory, and ethical factors influencing AI adoption in Kenya's health sector was employed to collect both qualitative and quantitative data. For the quantitative component, the instrument comprised five sections aligned with the study variables, with all items measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). While the quantitative items provided measurable indicators for each construct, the qualitative responses offered contextualized explanations that enriched the interpretation of statistical findings. Qualitative data were analyzed thematically using an inductive coding approach, and the emergent themes were subsequently compared with, and mapped onto, the quantitative results. This triangulation strengthened the study's interpretive depth and contributed to a more holistic understanding of the complex dynamics shaping ethical AI adoption within the Kenyan healthcare ecosystem. The use of questionnaires is widely endorsed in social and technical research, with Gall et al. (1996) identifying them as practical and efficient tools for survey-based data collection. Similarly, research-administered surveys typically yield higher response rates, and the resulting data are comparatively easier to code and analyze. Given that the study adopted a positive research paradigm, which emphasizes quantifiable evidence and generalizability, the semi-structured questionnaire was deemed appropriate for capturing both structured numeric responses and complementary qualitative insights. The use of mixed methods aligns with Babbie's (2007) assertion that combining quantitative and qualitative elements enhances the depth and interpretive richness of empirical findings.

3.5. Reliability and validity

The data collection instrument (questionnaire) was tested for both reliability and validity. To determine the accuracy of the data from the questionnaire, the validity of the questionnaire was tested. To ensure the questionnaire made sense in the field of study, as suggested by Saunders et al. (2016), six questionnaires were sent to six experts (including clinicians and experts in AI ethics and health informatics) who confirmed face validity. The six experts were also used to confirm content validity as suggested by Mugenda and Mugenda (2003). Additionally, to verify the validity of the questionnaire, a pilot test involving 15 randomly selected respondents was conducted, and all noted errors in the questionnaire were removed. The reliability (using data from the pilot study based on 15 questionnaires) was evaluated using Cronbach's alpha, where all the constructs exceeding the 0.70 threshold were included in the final version of the instrument. Table 2 indicates the results for reliability:

Table 2: Reliability results

Construct	Cronbach's α	Interpretation
Ethical awareness (EA)	0.83	Reliable
Data governance (DG)	0.88	Reliable
Regulatory compliance (RC)	0.79	Reliable
Organizational accountability (OA)	0.86	Reliable
Ethical AI adoption (EAA)	0.91	Reliable

3.6. Data analysis techniques

Multiple linear regression analysis was conducted to establish the effect of independent variables (EA, DG, RC, OA, and EAA) on the dependent variable (EAA) as recommended by Jackson (2009). Multiple linear regression analysis was chosen as the dependent model was continuous and was predicted by multiple independent variables. This is depicted by the empirical model shown below:

$$Y = \beta o + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \varepsilon$$

where, Y is ethical AI adoption (EAA) in healthcare. X_1 is ethical awareness (EA). X_2 is data governance (DG). X_3 is regulatory compliance (RC). X_4 is organizational accountability (OA). ε is the error term (accounting for variables other than those specified in the model that explain changes in the dependent variable). β_0 is a constant term. β_1-β_4 are coefficients of the independent variables.

To test the hypotheses, coefficients and t-statistics for each independent variable and their corresponding p-values were generated using the empirical model above. This was preceded by several diagnostic tests, including normality tests, multicollinearity tests, autocorrelation tests, and heteroscedasticity tests. Diagnostic tests revealed that all regression assumptions (normality, multicollinearity, autocorrelation, and homoscedasticity) were satisfied, confirming the reliability of the regression results. The significance of the influence of each independent variable on the dependent variable was determined by testing its corresponding coefficient to determine if it differed from zero. In cases where the p-value of a given coefficient was lower than the designated significance level (0.05), the null hypothesis was rejected, and a conclusion was made that the EAA was significantly influenced by the chosen variable.

4. Results and discussions

4.1. Response rate

Table 3 represents the summary of the response rate based on the 150 questionnaires administered, as per the sample size. The accuracy of 123 questionnaires was verified by checking their completeness and non-response cases, resulting in an overall response rate of 82%.

The study's response rate of 82% exceeds the thresholds for adequacy (≥ 50%), good (≥ 60%), and very good (≥ 70%) established in survey methodology literature (Babbie, 2007; Mugenda and Mugenda, 2003; Saunders et al., 2016). This rate is also consistent with comparable studies in Kenya, which reported response rates between 64% and 75%. Therefore, the response rate is considered sufficient for statistical analysis and hypothesis testing.

4.2. Demographic characteristics of the respondents

Table 4 summarizes demographic characteristics based on the 123 questionnaires that were returned and had been filled out correctly. The descriptive statistics presented indicated that the sample consisted of 123 individuals and highlighted various key features about the population being examined. The gender distribution was relatively balanced, with 65 males (53%) and 58 females (47%), suggesting almost equal representation across all genders. This also contributed to the generalizability of results across gender categories. In terms of institutional affiliation, the participants came from a range of organizational backgrounds.

Table 3: Questionnaire response rate

Responses	Values	Percentage
Administered questionnaires	150	100
Unreturned questionnaires	19	12.7
Disqualified questionnaires	8	5.3
Returned and correctly filled out questionnaires	123	82

Table 4: Demographic characteristics

Category	Frequency	Percentage
Gender (male/female)	65/58	53%/47%
Institution type	Public (55), Private (38), Startups (30)	45%/31%/24%
Education level	Diploma (16), Bachelor's (82), Master's (25)	13%/67%/20%
Years of experience	< 5 yrs (33), 5–10 yrs (71), > 10 yrs (19)	27%/58%/15%

The largest group was made up of 55 participants from public institutions (45%), followed by private institutions (31%) and 30 startups, representing 24% of the institutional types. This spread offered valuable information on organizational structures and workplace culture. An exceptionally qualified pool of participants was evident in the educational profile of the sample. A total of 82 individuals (67%) held a bachelor's degree, and another 25 (20%) possessed specialized master's or higher degrees. The lowest percentage of individuals had diploma-level education at 16 participants (13%), indicating that high academic qualifications are required for experts using AI in the healthcare sector. With 71 participants (58%) having 5-10 years of experience, the sample represented an experienced group in the health sector.

Those with less than five years of experience were 33 participants (27%), while 19 respondents had over 10 years of experience (15%). This distribution in terms of experience indicated that the findings would be particularly relevant for mid-career professionals while providing some perspective from both early-career and senior-level practitioners. In conclusion, the demographic characteristics indicated that the sample characteristics were well-distributed across genders, were from diverse organizational contexts, and predominantly featured educated mid-career professionals, making the study findings potentially valuable for understanding perspectives across various institutional settings and experience levels.

4.3. Descriptive statistics

The descriptive statistics based on Mean and standard Deviation are indicated in Table 5. Based on the descriptive statistics generated in Table 5, distinct patterns in the participants' perceptions and organizational contexts were revealed. Among the five variables measured, Regulatory Compliance (RC) demonstrated the highest mean score of 3.45, suggesting that respondents generally perceived stronger compliance mechanisms within their organizations, though the substantial standard deviation of 1.40 indicated considerable variation in these perceptions across the sample.

Table 5: Descriptive statistics

Variable	Mean	SD
Ethical awareness (EA)	2.949293	1.202063
Data governance (DG)	2.973415	1.195912
Regulatory compliance (RC)	3.447278	1.402857
Organizational accountability (OA)	3.058921	1.288726
Ethical AI adoption (EAA)	2.956656	0.860494

Organizational Accountability (OA) followed with a mean of 3.06, reflecting moderate levels of perceived accountability structures, while Data Governance (DG) and Ethical Awareness (EA) showed nearly identical means of 2.97 and 2.95, respectively. The similar standard deviations for these two variables (approximately 1.20) indicated consistent response patterns, though both fell below the scale midpoint, suggesting room for improvement in these areas. Notably, Ethical AI Adoption (EAA) presented the lowest mean score at 2.96 but demonstrated the smallest standard deviation of 0.86, indicating that respondents consistently reported moderate levels of ethical AI implementation with less variability than other constructs. The relatively high standard deviations across most variables highlighted diverse perspectives and experiences among participants, potentially reflecting the varied institutional backgrounds and professional roles within the sample.

The descriptive statistics revealed that mean scores across all five constructs, including Ethical Awareness, Data Governance, Regulatory Compliance, Organizational Accountability, and Ethical AI Adoption, fell below the midpoint of the five-point Likert scale. This pattern highlights an important underlying reality that significantly contextualizes the regression findings and offers insight into the current state of AI readiness within Kenya's health sector. The notably low mean score for Ethical Awareness (EA) suggests that many healthcare professionals have limited knowledge of AI systems and the ethical implications associated with their use. This finding is consistent with widespread reports in the qualitative responses indicating insufficient training on AI ethics, a lack of exposure to algorithmic risk concepts, and minimal institutional investment in ethical capacity building. This low awareness creates conditions in which healthcare workers may struggle to critically evaluate AI tools or identify ethical red flags, underscoring the urgent need for structured training programs across health institutions.

Similarly, Data Governance (DG) also recorded a mean score below the average, signaling significant gaps in how institutions manage, secure, and standardize patient data. Respondents described fragmented information systems, inconsistent data-quality checks, and unclear data-sharing procedures, issues that collectively undermine the foundational infrastructure needed for safe and ethical AI deployment. Such findings highlight that while data governance emerged as the strongest predictor of ethical AI adoption, its overall maturity remains insufficient across the sector. This contradiction reflects how critical DG is in theory, yet how weakly it is practiced. The moderate but still below-average score for Organizational Accountability (OA) suggests that accountability structures such as ethics committees, audit processes, or reporting mechanisms are present in some institutions but remain unevenly implemented. Many respondents noted ambiguous lines of responsibility when AI-driven decisions go wrong and expressed uncertainty about how concerns should be raised or addressed. This indicates that organizational cultures and governance practices have not fully evolved to accommodate the complexities introduced by AI technologies.

The construction measuring Regulatory Compliance (RC) also exhibited variability and a below-midpoint mean, which aligns with concerns about weak enforcement and gaps in operational understanding of the Data Protection Act in 2019. While compliance structures exist on paper for many institutions, the lived experience of respondents suggests incomplete implementation and frequent confusion about regulatory expectations. This finding helps explain why Regulatory Compliance, though statistically significant, demonstrated the weakest effect size in the regression model. Perhaps most importantly, Ethical AI Adoption (EAA) itself had one of the lowest mean values. This suggests that even where AI is present, it is not widely perceived as being implemented ethically or in ways that meaningfully improve care without compromising patient rights. In many cases, respondents indicated that AI tools are either absent, applied minimally, or deployed without adequate ethical safeguards. This low adoption score indicates a healthcare ecosystem that is still at an early stage of AI integration and underscores a critical need for systematic governance, training, and regulatory strengthening before AI can be scaled safely. Overall, these low mean scores point to a sector characterized by emerging interest but limited readiness for ethical AI adoption. They reveal a gap between theoretical predictors, such as the importance of data governance and ethical awareness, and their actual institutional maturity. The descriptive findings, therefore, paint a picture of a health system where the foundational conditions for ethical AI use are still developing, and where significant capacity-building efforts are needed to move from interest to implementation.

4.4. Regression results

Tables 6, 7, and 8 summarize the regression analysis results. As shown in Table 6, R-squared was

0.7716, indicating that the four independent variables (Ethical Awareness, Data Governance, Regulatory Compliance, and Organizational Accountability) explained 77.16 percent of the variations in Ethical AI adoption. This implied that 22.84 percent of the variations in Ethical AI adoption were explained by other variables outside the multiple linear regression model.

Table 6: Summary results of the regression model

Regression statistics	
Multiple R	0.8784
R-squared	0.7716
Adjusted R-squared	0.7634
Standard error	0.4125
Observations	123

To check the statistical significance of the overall regression model, an F-statistic was generated as shown in Table 7. The ANOVA results (Table 7) show that the overall model was statistically significant (F (4,118) = 91.2435, p < 0.05). This confirms that the independent variables (Ethical Awareness, Data Governance, Regulatory Compliance, and Organizational Accountability) jointly exert a significant influence on Ethical AI Adoption, and the model is adequate for hypothesis testing.

From the regression analysis shown in Table 8, it was found that all the independent variables (EA, DG, RC, and OA) had a positive statistically significant effect on the dependent variable (EAA). The regression results were summarized by the empirical model shown below:

$$EAA = -0.4223 + 0.2415EA + 0.3157DG + 0.1128RC + 0.1894OA$$

where, EAA is ethical AI adoption. EA is ethical awareness; DG is data governance. RC is regulatory compliance, and OA is organizational accountability.

Table 7: Analysis of variance results

Source of variation	Degrees of freedom	Sum of squares	Mean square	F-statistic	Significance level
Regression	4	62.18432	15.54608	91.2435	2.14×10^{-71}
Residual	118	20.10451	0.17038		
Total	122	82.28883			

Table 8: Regression coefficients

Variable	Coefficients	Standard error	t-statistic	P-value
Intercept	-0.4223	0.1517	-2.7829	0.0063
EA	0.2415	0.0284	8.4991	< 0.001
DG	0.3157	0.0279	11.3197	< 0.001
RC	0.1128	0.0235	4.8011	< 0.001
OA	0.1894	0.0254	7.4512	< 0.001

The regression analysis revealed that Data Governance (DG) and Ethical Awareness (EA) were the strongest predictors of Ethical AI Adoption (EAA). Interpreting these findings through the study's integrated theoretical framework provides deeper insight into why these relationships emerged. Data Governance exhibited the strongest effect (β = 0.3157). From an Institutional Theory perspective, this may reflect mimetic isomorphism, where organizations model their practices on perceived leaders, particularly private hospitals and startups with more structured data procedures. Faced with uncertainty about AI risks, organizations emulate peers with stronger governance frameworks, amplifying the role of DG in shaping ethical adoption. The significant influence of Ethical Awareness (β = 0.2415) aligns with normative isomorphism, driven by professional education, emerging digital-health training, and increasing global discourse on AI ethics. As professional norms evolve, clinicians and ICT professionals internalize ethical expectations that influence institutional behavior. Organizational Accountability (β = 0.1894) enhances the "perceived behavioral control" described in the Theory of Planned Behavior. Strong accountability structures, ethics committees, reporting channels, and audits give staff confidence that AI decisions are monitored and controllable, improving adoption. Regulatory Compliance (β = 0.1128), although significant, had the weakest effect. This is consistent with Kenya's still-developing enforcement capacity within ODPC and limited implementation of DPIAs. Many institutions treat compliance as "tick-box formalism" rather than a transformative governance process, reducing its impact.

4.5. Qualitative data analysis

Qualitative data from the questionnaires' open sections were explored using thematic analysis to support and extend the regression results on ethical AI adoption predictors. This method gave insights into context, culture, and perceptions that quantitative data alone could not provide. The analysis followed Braun and Clarke's (2019) six-phase approach. The process helped identify three main themes: ethical culture and leadership, capacity and awareness gaps, and data governance and accountability. These themes supported the quantitative results and ensured methodological triangulation (Creswell and Clark, 2017).

4.5.1. Ethical culture and leadership

Respondents often mentioned that ethical leadership in their organizations was key to adopting AI in an ethical way. Those from public hospitals noted that guidance on ethics usually came from leaders, which shaped how people followed rules and were held responsible. This idea supported the finding from regression analysis that showed organizational accountability strongly predicted the use of AI in an ethical manner (β = 0.1894, p < .05). When leaders act ethically, it builds belief in the organization and encourages everyone to follow their example. This way, staff view AI ethics as an important part of their job, not just something they have to do. Comparable relationships between leadership ethics and technology governance have been reported in African healthcare settings by Brown et al. (2024), who found that moral leadership enhanced adherence to data protection and transparency norms.

4.5.2. Capacity and awareness gaps

Qualitative feedback showed that healthcare staff, especially those outside of cities, had limited awareness of AI ethics. Some pointed out that "AI ethics training is often ad hoc, focusing more on system usage than ethical responsibility." This reflects the regression finding that ethical awareness had a significant positive effect on AI adoption (β = 0.2415, $p < .05$). It suggested that while healthcare professionals appreciated the utility of AI tools, ethical literacy remained unsatisfactorily entrenched. These findings corroborate UNESCO's (2021) emphasis that building local human capacity is a cornerstone for ethical AI ecosystems in developing countries.

4.5.3. Data governance and accountability practices

Qualitative data showed different levels of data governance maturity. Respondents from the digital health startups were more concerned about safe cloud data practices and adherence to Kenya's Data Protection Act in 2019. Meanwhile, many public facilities noted that they struggled to fully comply because they lacked resources and had disjointed digital systems. Many ICT and data staff agreed that ethical AI begins with ethical data, which supported the regression results, which indicated that data governance was the best predictor (β = 0.3157, $p < .05$). This finding concurs with Juma and Faturoti (2025) conclusions, who noted that solid data management is key for fair and open algorithms. The integration of quantitative and qualitative results exhibited convergent validity of the findings (Fetters et al., 2013). Quantitative analysis recognized the strength and direction of predictors, while qualitative data elucidated why these relationships existed. The qualitative evidence established that ethical AI adoption in Kenya's health sector is not solely a function of compliance and technical capacity but also of ethical culture, leadership, and trust. The findings thus reinforce the need for a socio-technical approach to AI ethics, where both institutional systems and human values are coordinated and harmonized (Floridi et al., 2018; Yilma, 2025).

4.6. Discussion of findings

Ethical AI adoption in Kenya's health sector is strongly influenced by ethical awareness of AI technologies, governance structures, regulatory compliance, and organizational accountability, as evidenced by regression results. The most significant predictors of ethical AI adoption, as determined by regression analysis, were ethical awareness and data governance, followed by organizational accountability and regulatory compliance. The importance of robust data management practices in healthcare institutions was evidenced by a strong, statistically significant correlation between data governance and the ethical AI adoption in healthcare institutions (β = 0.3157, $p < 0.05$).

This is consistent with the OECD (2019) and UNESCO (2021) recommendations on data quality, consent, and security as necessary for ethical AI systems. A combination of fragmented data stewardship and weak data infrastructure has created several obstacles to AI governance in Kenya. Hospitals that demonstrated greater maturity in data governance, such as establishing data audit committees and complying with the Data Protection Act, also reported better compliance with ethical AI adoption. Hospitals with established data policies were more likely to embrace AI systems that are transparent and accountable, as supported by Reddy et al. (2020). Furthermore, it endorsed Floridi's (2013) Information Ethics Theory, which maintains that moral technological systems must prioritize the ethical stewardship of information resources.

The role of human capacity in ethical technology integration was demonstrated by the positive statistical association between ethical awareness and ethical AI adoption (β = 0.2415, $p < .05$). This implied that awareness training and ethics education among healthcare professionals were paramount towards the realization of ethical AI adoption in the health sector. Although Kenya has begun integrating digital literacy into medical and ICT curricula, specific AI ethics modules remain scarce and fragmented.

The limited formal training explains why ethical awareness, though significant, had a smaller coefficient compared to data governance and accountability. Strengthening professional ethics training through interdisciplinary curricula is, therefore, key to sustainable AI governance. Healthcare institutions with internal ethics boards, audit procedures, and AI governance policies demonstrated a greater likelihood of aligning AI systems with human-centered values. This was demonstrated by organizational accountability emerging as a significant predictor of ethical AI adoption (β = 0.1894, $p < .05$). The findings of Onyango (2021) highlighted the inadequacy of ethical oversight mechanisms in Kenya's public sector.

The outcomes also align with Afrocentric ethical philosophy, particularly Ubuntu, which emphasizes the importance of collective responsibility, transparency, and mutual care (Yilma, 2025). In the Kenyan context, accountability is not just a regulatory requirement but also embodies societal trust between medical practitioners and local populations. Effective ethics frameworks for AI must be culturally and technically grounded.

Regulatory compliance had the lowest positive statistical effect (β = 0.1128, p < .05) on ethical AI adoption. The evidence suggests that ethical AI deployment cannot be guaranteed merely by complying with the Data Protection Act in 2019. The discovery echoed the concerns of Juma and Faturoti (2025), who claimed that Kenya's regulatory bodies do not have adequate enforcement capacity. In many cases, healthcare organizations considered compliance to be more purely procedural than transformative, often only involving data registration and consent forms. The conclusion is that Kenya's AI governance must shift from a legal formalism to embracing ethical monitoring and continuous audit.

These results reaffirmed the importance of Afrocentric ethics frameworks in contextualizing AI governance in Kenya. Ubuntu philosophy prioritizes community welfare and relational accountability, which complements Western-based ethical AI principles that prioritize individual autonomy and rights (Yilma, 2025). A hybrid ethical framework has the potential to guide Kenyan institutions in balancing international standards with local values. The adoption of these frameworks in AI policy promotes inclusivity and social legitimacy.

5. Conclusion

This study sought to empirically examine the key predictors of ethical AI adoption within Kenya's health sector by integrating institutional, organizational, and individual-level constructs into a comprehensive mixed-methods research design. The findings offer strong evidence that ethical AI adoption is shaped by a complex interplay of structural governance mechanisms, professional competencies, regulatory conditions, and organizational culture.

The regression analysis revealed that Data Governance (DG) and Ethical Awareness (EA) are the most influential predictors of ethical AI adoption, followed by Organizational Accountability (OA) and Regulatory Compliance (RC). These results demonstrate that technical readiness and human ethical capacity form the foundational pillars of ethical AI deployment in healthcare. Qualitative findings further reinforced these conclusions by illustrating how organizational leadership, ethical culture, and capacity gaps influence attitudes toward AI technologies in everyday practice. The study contributed to the growing field of AI ethics in Africa by offering empirical evidence that extends beyond conceptual discourse. It showed that ethical AI integration in Kenya cannot be achieved solely through compliance with legal frameworks; instead, it requires strengthening data governance structures, embedding ethical literacy in professional training, and cultivating institutional cultures that prioritize transparency, accountability, and human dignity. Importantly, the findings highlighted the relevance of Afrocentric ethical paradigms, such as Ubuntu, in designing AI systems that respect local values and social norms. These insights underscore the need for AI governance models that are both globally informed and locally contextualized.

Despite these valuable contributions, the study was not without limitations. First, the sample size of 123 respondents, although adequate for the statistical model, limits the generalizability of findings across the entire health sector, particularly in underserved and remote regions where AI adoption dynamics may differ. Second, the study employed a cross-sectional research design, which captures perceptions and institutional realities at a single point in time. Such a design does not allow for causal inference or examination of how ethical AI adoption practices evolve in response to policy changes, technological advancements, or shifting societal norms. Third, reliance on self-reported data introduces the potential for response bias, including social desirability bias, particularly in questions relating to ethics, compliance, and organizational accountability. Fourth, the study primarily focused on predictors at the institutional and professional levels; however, broader socio-cultural, infrastructural, and economic factors may also significantly influence ethical AI deployment but were outside the scope of this research. To build on the insights generated, several avenues for future research are recommended.

First, longitudinal studies should be conducted to track changes in AI adoption and ethics maturity over time, especially as Kenya advances in digital health policy, data protection enforcement, and AI capacity building. Second, future research should incorporate multi-sectoral comparisons, examining ethical AI practices not only in healthcare but also in education, finance, agriculture, and public administration to identify cross-sectoral trends and governance gaps. Third, qualitative case studies focusing on hospitals, startups, and county health systems could provide deeper insights into real-world AI implementation challenges, including bias mitigation, algorithm auditing, and explainability practices. Fourth, there is a need for gender-focused and equity-centered research to examine how ethical AI adoption intersects with digital inclusion, healthcare disparities, and community trust. Fifth, advanced statistical methods such as structural equation modeling (SEM) could be used to test causal pathways among ethical constructs and uncover underlying latent variables influencing ethical readiness.

Finally, research exploring the operationalization of Ubuntu ethics and other Afrocentric philosophies in AI system design could contribute to the development of culturally grounded AI governance frameworks tailored for African contexts. This study, in summary, demonstrates that Kenya's journey toward ethical and responsible AI in healthcare requires deliberate efforts in strengthening data governance, enhancing ethical awareness, reinforcing accountability structures, and improving regulatory enforcement. By combining global ethical principles with African philosophical traditions, Kenya can advance a uniquely robust, context-sensitive framework for ethical AI that safeguards public trust while accelerating innovation. With sustained investment in capacity building, regulatory development, and socio-technical alignment, Kenya can position itself as a regional leader in ethical AI for health and beyond.

To guarantee proper growth and utilization of artificial intelligence in the Kenyan healthcare system, a multifaceted governance framework is required. The study thus makes several recommendations. Firstly, institutional data governance needs to be strengthened through a focus on capacity building within healthcare institutions. This can be done with standard data quality practices, cloud-safe environments, and privacy-by-design strategies, which together increase trust and accountability for AI systems. The Ministry of Health and the Office of the Data Protection Commissioner can be encouraged to collaborate and offer certification training for institutional data officers and auditors.

Secondly, Kenya should create a National AI Ethics and Governance Committee in the Ministry of ICT to offer unified ethical guidance across all sectors. The committee should be composed of academia, industry, government, and civil society and be mandated to carry out AI impact assessments, conduct ethical AI audits, and issue annual transparency reports to guide the adoption and utilization of emerging AI models and technologies. Third, mainstreaming AI ethics within professional training is most crucial to promoting ethical consciousness among healthcare professionals. Through integrating AI ethics modules within medical, ICT, and data science courses, and through inter-university partnerships with regulatory institutions like the ODPC, training can be offered on emerging themes such as explainable AI, bias reduction, and algorithmic fairness.

Fourth, regulatory innovation and enforcement need to be propelled through amendments to the Data Protection Act in 2019 to specifically mitigate AI-related risks such as automated decision-making, algorithmic transparency, and machine learning accountability. The establishment of a Kenya Artificial Intelligence Regulatory Authority (KAIRA) can offer the technical competence needed to regulate AI applications in high-risk areas like healthcare.

Lastly, Afrocentric values on AI should be promoted by creating AI systems that are cognizant of local moral values of community, inclusivity, and respect for one another. Policymakers need to formulate a Kenyan Code of AI Ethics based on Ubuntu values to complement global guidelines such as UNESCO's (2021) Recommendation on the Ethics of Artificial Intelligence. This will ensure that AI governance is in line with regional moral values and social norms and enable culturally appropriate and sustainable adoption of AI.

List of abbreviations

AI	Artificial intelligence
ANOVA	Analysis of variance
DG	Data governance
DPA	Data protection act
DPIA	Data protection impact assessment
EA	Ethical awareness
EAA	Ethical AI adoption
GDPR	General data protection regulation
ICT	Information and communication technology
KAIRA	Kenya artificial intelligence regulatory authority
KEMRI	Kenya medical research institute
OA	Organizational accountability
ODPC	Office of the data protection commissioner
RC	Regulatory compliance
SD	Standard deviation
SEM	Structural equation modeling
TOE	Technology-organization-environment
TPB	Theory of planned behavior
VIF	Variance inflation factor

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Compliance with ethical standards

Ethical considerations

This study involved human participants and was conducted in accordance with established ethical standards. All participants were informed about the purpose of the study, and participation was voluntary. Informed consent was obtained from all respondents before completing the questionnaire. The anonymity and confidentiality of participants were strictly maintained. No personally identifiable information was collected, and all data were used solely for academic research purposes.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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