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Evaluating the Ethical Practices in Developing AI and Ml Systems in Tanzania

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***Abstract**: Artificial Intelligence (AI) and Machine Learning (ML) present transformative opportunities for sectors in developing countries like Tanzania that were previously hindered by manual processes and data inefficiencies. Despite these advancements, the ethical challenges of bias, fairness, transparency, privacy, and accountability are critical during AI and ML system design and deployment. This study explores these ethical dimensions from the perspective of Tanzanian IT professionals, given the country's nascent AI landscape. The research aims to understand and address these challenges using a mixed-method approach, including case studies, a systematic literature review, and critical analysis. Findings reveal significant concerns about algorithm bias, the complexity of ensuring fairness and equity, transparency and explainability, which are crucial for promoting trust and understanding among users, and heightened privacy and security risks. The study underscores the importance of integrating ethical considerations throughout the development lifecycle of AI and ML systems and the necessity of robust regulatory frameworks. Recommendations include developing targeted regulatory guidelines, providing comprehensive training for IT professionals, and fostering public trust through transparency and accountability. This study underscores the importance of ethical AI and ML practices to ensure responsible and equitable technological development in Tanzania.*

***Keywords**: Bias in Artificial Intelligence, Algorithmic Fairness, Ethics in Machine Learning, Machine Learning.*

1. INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) have heralded significant progress across various sectors, offering a promising future for developing countries like Tanzania. However, before the advent of AI and ML, sectors relied on manual processes, human expertise, and traditional data analysis, leading to inefficiencies and inconsistencies [1]. Diagnoses and treatment plans heavily rely on medical professionals' experience and intuition, resulting in varying care quality [2]. In criminal justice, risk assessment and sentencing decisions were based on precedent and guidelines, often overlooking individual circumstances and potential biases [3]. Data processing could have been more laborious and time-consuming, making it challenging for organisations to extract insights from large datasets, leading to missed opportunities for innovation [4]. Privacy concerns were prevalent due to less sophisticated data handling practices and limited safeguards for protecting sensitive information. The absence of AI and ML hindered progress in sectors where data-driven decision-making could have a significant societal impact, underscoring the need for technological advancements to address these challenges.

This study delves into these ethical dimensions within Tanzania, where AI adoption is still in its early stages. Given the country's unique technological landscape, regulatory framework, and cultural context, it is imperative to address these ethical challenges from the perspective of IT professionals. Tanzania expects to start conducting online job interviews organized by the public service recruitment secretariat. Developing systems for conducting interviews and other systems for different uses requires intelligent systems to care for authentications and detect cheating. AI is well-suited for authentication and preventing cheating in online interviews due to its ability to analyse biometric data for identity verification and monitor for suspicious behaviours in real time, ensuring the integrity of the interview process. This study examines the implications of these considerations for AI and ML projects in Tanzania. The goal is to provide information for developing regulatory frameworks, offer support and training for IT professionals, and ultimately build public trust. This will be achieved by addressing the following questions:

> *How do IT professionals in Tanzania perceive and address ethical challenges—such as bias, fairness, transparency, privacy, and accountability—in developing and deploying AI and ML technologies?*

The main goal is to promote the ethical development and deployment of AI and ML technologies tailored to Tanzania's context. This study seeks to understand Tanzania's ethical considerations when adopting and developing its AI and ML projects. This study is timely and essential because Tanzania is in the early stages of AI adoption. Addressing ethical challenges is crucial to ensuring responsible and equitable technological development.

Adopting AI and ML applications has brought forth new challenges, underscoring the critical importance of ethical considerations. These concerns, including bias, fairness, transparency, privacy, and accountability, are not mere technicalities but the very pillars upon which the positive societal outcomes of these technologies rest. They are particularly pertinent during the design stage of AI and ML systems. Numerous studies have underscored these concerns across different domains. For instance, Applegarth et al. [3] have highlighted that bias in AI algorithms can perpetuate systemic inequalities, significantly impacting areas like healthcare and criminal justice. Fairness, intricately linked to bias, necessitates equitable treatment, as Tierney [5] discussed. Additionally, Manure et al. [6] and Balasubramaniam et al. [7] have emphasized the importance of transparency in building trust and understanding algorithmic outcomes. Finally, as Novelli et al. [8] have stressed, accountability is vital in ensuring responsible AI use.

The study contributes significantly to the understanding and advancement of AI and ML ethics within the context of developing countries, specifically Tanzania. By highlighting the unique ethical challenges and considerations in AI adoption, this research underscores the necessity of ethical scrutiny and regulatory frameworks tailored to the local context. It provides a foundational perspective on the perceptions and practices of Tanzanian IT professionals regarding bias, fairness, transparency, privacy, and accountability in AI and ML technologies. The findings offer valuable insights for policymakers, educators, and technology developers, aiding in creating robust, context-specific guidelines and training programs. This study is crucial in fostering public trust, promoting responsible AI development, and ensuring that the integration of these advanced technologies contributes positively to societal progress in Tanzania.

2. LITERATURE REVIEW

This literature review aims to delve into the wealth of knowledge and insights amassed by AI and ML scholars, researchers, and experts. It aims to comprehensively explore and analyse the existing scholarship on AI and ML, elucidating key findings, trends, and gaps in understanding. By undertaking this exploration, the study seeks to establish a robust foundation for research endeavors within this dynamic and rapidly evolving field.

2.1 Bias in AI and ML

Bias in AI and ML algorithms, arising from unfair assumptions or preferences in data or model design, poses significant ethical concerns [9]. This bias can manifest in various forms, leading to discriminatory outcomes and perpetuating societal inequalities [10]. For instance, facial recognition algorithms trained on biased datasets may perform poorly on faces of certain ethnicities [11]. Biased algorithms in hiring processes can discriminate against candidates based on race or gender, hindering diversity efforts [12]. Moreover, biased algorithms erode trust in AI systems, leading to scepticism and user resistance [9]. Addressing bias in AI and ML is crucial for ensuring fairness, transparency, and accountability in decision-making processes [8]. Therefore, these must be addressed during the deployment of AI and ML.

2.1.1 Algorithmic bias in the Tanzanian context

In the Tanzanian context, biases in AI and ML are shaped by unique socio-cultural, economic, and infrastructural factors that differentiate them from those observed globally. Data representation bias is a significant concern due to local data's limited availability and quality. Many AI and ML models, such as decision tree algorithms used in healthcare, are trained on datasets from developed countries [13], leading to suboptimal performance and biased outcomes for the Tanzanian population. For instance, healthcare algorithms trained on non-representative data may misdiagnose diseases more prevalent in Tanzania or misinterpret common genetic variations. Socio-economic disparities further exacerbate biases in AI and ML systems. Financial inclusion algorithms, like logistic regression credit scoring models, may disadvantage individuals without formal financial histories, often in rural and low-income urban areas, perpetuating existing inequalities and making it harder for marginalized groups to access credit, insurance, or other financial services.

Language and cultural biases are also prominent, as most AI and ML systems using Generative Pre-trained Transformer 3 are designed for widely spoken languages and cultural contexts [14]. In Tanzania, where Swahili is the national language and numerous local dialects are spoken, this bias can significantly impact the effectiveness of natural language processing applications. Algorithms like BERT-based models may need to be revised to understand cultural nuances, idioms, and local contexts, leading to inaccuracies in automated customer support, translation, and sentiment analysis. Additionally, technological infrastructure biases arise from assumptions of high-speed internet access and widespread smartphone usage, which may not hold in regions with limited connectivity; according to [15], this disproportionately affects rural populations. Educational bias, stemming from varying levels of digital literacy, limits the benefits of AI and ML technologies to more educated and tech-savvy populations [16]. Lastly, policy and regulatory biases due to a less mature regulatory environment can lead to unregulated use and potential misuse of AI technologies, creating disparities in deployment and governance compared to countries with more established frameworks.

AI and ML systems must account for diverse populations and contexts. However, the peculiar biases present in Tanzania highlight the importance of localized data, culturally aware algorithms, and context-sensitive implementations. Addressing these biases requires concerted data collection, algorithm design, and policy-making efforts to ensure that AI and ML solutions are equitable and effective across different regions.

2.2 Fairness and Equity in AI and ML Systems

Fairness and equity are foundational principles in the ethical development of AI and ML systems, essential for upholding justice, non-discrimination, and human rights [5, 17]. Fairness entails that algorithmic decisions should not systematically disadvantage individuals based on protected characteristics, while equity ensures equal opportunities for all [17]. Trust and credibility in AI systems hinge on perceptions of fairness, fostering acceptance of outcomes, and promoting social cohesion [7]. However, achieving fairness and equity in AI and ML poses significant challenges. Algorithmic complexity complicates bias detection and mitigation, exacerbated by opaque decision-making processes [18]. Additionally, biased training data can perpetuate discriminatory outcomes, while subjective interpretations of fairness hinder universal criteria development [19, 20].

Various strategies address bias and promote fairness. Fairness-aware algorithms explicitly consider fairness during model design, adjusting predictions to achieve equitable outcomes [21]. Techniques like data augmentation and balancing mitigate biases in training data, ensuring fairness across demographics [22]. Transparent and interpretable AI models enhance accountability and facilitate scrutiny of algorithmic decisions [7]. Moreover, diversity and inclusivity in AI research mitigate biases by identifying blind spots overlooked by homogeneous groups, enhancing the robustness and equity of AI solutions [23]. Despite challenges, these approaches offer pathways to mitigate bias and promote fairness in AI and ML systems, which is crucial for their ethical development and societal impact.

2.3 Transparency and Explainability in AI and ML Models

Transparency and explainability are crucial in ethical AI and ML development. They enable users to understand decisions and challenge biased outcomes [8]. Transparency refers to openness in AI systems, allowing scrutiny of processes and data-driving decisions, while explainability provides interpretable justifications for outcomes [7]. In high-stakes contexts like healthcare or finance, individuals impacted by AI decisions have a right to understand and contest outcomes, fostering accountability and trust [7]. Techniques like interpretable machine-learning models or post hoc explainability methods offer insights into decision factors, enhancing transparency [6, 24]. Opaque AI systems raise ethical concerns, hindering accountability and exacerbating biases [25, 26]. With openness, holding developers accountable for errors or biases becomes easier, eroding trust in decision-making processes [26]. Lack of transparency also limits interdisciplinary collaboration, impeding progress in critical sectors like healthcare [27].

2.4 AI and ML Technologies into Other Applications

Integrating AI and ML technologies offers unprecedented efficiency gains by automating tasks and processing vast data volumes swiftly [28]. Their prowess in analyzing complex datasets improves decision-making, transforming industries from enhancing customer experiences to revolutionizing healthcare [29]. Predictive maintenance reduces equipment downtime, enabling more innovative operations in today's data-driven world [30]. However, deploying AI and ML raises substantial privacy concerns due to extensive data usage [9]. These algorithms rely on personal data, potentially compromising privacy without consent [31]. Techniques like data mining may infer sensitive information, posing risks of unintended disclosure and discrimination [31]. The proliferation of AI and ML amplifies data breach risks, with large datasets becoming targets for malicious exploitation [29]. Breaches expose personal and financial information, leading to identity theft and fraud. Moreover, AI introduces new security vulnerabilities, like adversarial attacks manipulating models to compromise privacy.

2.5 Roles and Responsibilities of IT Professionals in Developing Trusted AI and ML Projects

IT professionals engaged in AI and ML projects carry ethical obligations to ensure these technologies' responsible development, deployment, and utilization. This encompasses embedding ethical considerations throughout the development lifecycle, from data collection to model validation, to address potential biases, ensure transparency, and integrate fairness and accountability mechanisms into system design [25, 26]. Thorough risk assessments are vital for identifying potential ethical, legal, and societal implications, requiring robust testing, validation, and continuous monitoring to mitigate risks associated with bias, privacy infringements, security vulnerabilities, and unintended consequences [32]. Engaging with diverse stakeholders, including end-users and policymakers, promoting transparency, and addressing concerns are crucial for fostering trust and accountability in AI and ML projects. Adherence to professional ethics codes and standards, prioritizing fairness, equity, and societal well-being, is paramount, ensuring integrity, honesty, and accountability in AI and ML technology development and deployment [25].

2.6 The Role of Governments and Regulatory Bodies Regarding AI and ML Accountability

Governments and regulatory bodies increasingly recognize the necessity of legal and regulatory frameworks to govern AI and ML accountability and ensure compliance with ethical standards and societal norms. These frameworks include robust data protection and privacy laws like the GDPR and CCPA, which impose legal obligations on organisations to secure individuals' data when using AI and ML technologies. Algorithmic accountability and transparency regulations, such as the EU's proposed Artificial Intelligence Act, mandate transparency and ethical use of AI systems to ensure fairness and accountability [33]. Liability and Tort Law are crucial in assigning responsibility for the harm caused by AI systems, holding developers and operators liable for negligence or defects. Ethical guidelines and best practices developed by professional associations and industry consortia guide the responsible and ethical use of AI and ML technologies, helping IT professionals navigate ethical dilemmas and comply with moral norms [25].

2.7 The importance of addressing these ethical challenges in AI and ML development

Addressing ethical challenges in AI and ML is crucial due to their profound societal impact. Neglecting bias, fairness, transparency, privacy, and accountability can perpetuate inequalities, erode trust, and undermine human rights [34]. Biased healthcare algorithms, for example, worsen disparities in diagnosis and treatment, compromising patient outcomes. Similarly, opaque AI in criminal justice can unfairly target communities, fostering discrimination [31]. Prioritizing ethics ensures these technologies benefit society, promoting fairness, equity, and ethical principles. Ethical AI practices foster innovation, sustainability, and responsible advancement [25]. They encourage collaboration, transparency, and accountability, enhancing system sustainability by mitigating bias and privacy risks [6]. Ethical development builds trust among stakeholders, encouraging long-term adoption and investment in AI and ML [17]. Integrating ethics is a moral and strategic necessity for their positive impact and sustainable growth in the digital age.

3. METHODOLOGY

The research utilized a mixed-method approach, incorporating both qualitative and quantitative methodologies. Case studies, a systematic review, and a Critical Analysis played crucial roles in supplementing and enriching this study.

3.1. Research Approach and Design

The study employed a primarily qualitative research approach, focusing on understanding complex AI and ML ethics phenomena. It utilized case studies and a systematic literature review to analyse the subject matter comprehensively. This approach facilitated an in-depth examination of ethical considerations while providing a broad overview of existing scholarly work.

3.2 Population and Sampling

The study did not target a specific population but examined a broad spectrum pertinent to AI and ML ethics. Therefore, the study employed purposive and snowball sampling techniques because the area of study is limited to a small number of specialists in this area. From 5 institutions, only 8 AI System developers were included in the study; the sample was taken from Ilala Municipal in Dar es Salaam City, Tanzania’s most prominent commercial city. According to Robinson [35], purposive sampling involves selecting participants based on specific characteristics or criteria relevant to the research. In contrast, snowball sampling relies on existing participants to recruit additional participants from their networks, which is useful when the population is hard to reach [36]. The study began with purposive sampling and selected initial participants who meet specific criteria relevant to your research. The participant must be an AI developer. Then, snowball sampling was used by asking these participants to refer others who also meet the criteria. This combined approach helped ensure a more comprehensive and representative sample [36].

3.3 Case Studies

This study incorporates case studies as a qualitative research method to provide in-depth insights into real-world examples of bias, fairness, transparency, and accountability issues in AI and ML systems. Case studies allow for examining specific instances or cases related to the topic under investigation. By analyzing concrete cases, researchers can identify patterns, underlying causes, and potential solutions to ethical challenges. The case studies were selected based on their relevance to the research questions and their ability to provide contextual richness and practical relevance.

3.4 Systematic Literature Review

A systematic literature review was conducted to gather and analyse the literature on AI and ML ethics. A rigorous methodology, including predefined criteria and keywords, was used to identify relevant studies from reputable sources while excluding predatory ones. The review aimed to comprehensively address ethical concerns in AI and ML across diverse fields for a thorough understanding of the topic.

3.5 Critical Analysis

The critical analysis systematically evaluated theories, concepts, and arguments in AI and ML ethics, scrutinizing prevailing discourses, ethical frameworks, and regulatory approaches. It uncovered underlying assumptions, biases, and implications, revealing gaps and contradictions in the literature and suggesting areas for future research and exploration.

4. RESULTS AND DISCUSSION

4.1 Case Studies and Real-world Examples

Case studies were employed to provide detailed examinations of real-world instances, offering contextual insights into the phenomena under investigation. Each case study provided a rich source of qualitative data, allowing for in-depth analysis and understanding of the complexities involved. Using multiple case studies facilitated a comprehensive exploration of various perspectives and scenarios, enhancing the study's validity and depth of analysis.

Case Study 1: Facial recognition bias

Background: A tech company developed a facial recognition system for law enforcement to identify suspects from surveillance footage. However, an independent audit revealed that the algorithm exhibited significant racial bias, leading to higher misidentification rates for individuals with darker skin tones [37, 38].

Ethical dilemma: The biased facial recognition system raised concerns about its potential to perpetuate systemic racial discrimination and unfairly target minority communities. Using such technology in law enforcement also raised questions about privacy, surveillance, and civil liberties.

Lessons learned: This case highlights the importance of rigorous testing and evaluation to identify and mitigate bias in AI algorithms, particularly those with significant societal implications. It underscores the need for transparency and accountability in developing and deploying AI systems and the importance of considering such technologies' broader societal impact.

Best practices: Organizations developing facial recognition systems should prioritize diversity. They should also ensure representativeness in their training data, conduct thorough bias assessments, and engage with diverse stakeholders, including civil rights groups and community organisations, to ensure their systems are fair, accurate, and trustworthy.

Case Study 2: Algorithmic hiring bias

Background: A large corporation implemented an AI-powered hiring tool to streamline its recruitment process and more efficiently identify top candidates. The case study used HireVue, which significantly impacts the recruitment AI industry and is an exemplary case study. As the longest-standing company in the AI recruitment market, HireVue has been a leading provider of video-based AI hiring tools for many years [39]. However, an analysis of the system's outcomes revealed that it disproportionately favored candidates from certain demographic groups, leading to concerns about bias and discrimination in the hiring process [9].

Ethical dilemma: The algorithmic hiring tool raised questions about fairness, equity, and meritocracy in employment practices. By perpetuating biases in historical hiring data, the system may have reinforced existing disparities in workforce diversity and perpetuated systemic inequalities.

Lessons learned: This case underscores the importance of transparency, accountability, and oversight in algorithmic decision-making processes, particularly in high-stakes domains such as hiring and employment. It highlights the need for organisations to critically evaluate the potential impact of AI systems on marginalized groups and take proactive steps to mitigate bias and promote fairness.

Best practices: Organizations should regularly audit their AI-powered hiring systems for bias and discrimination, involve human experts in the decision-making process, and provide avenues for recourse and appeal for individuals who believe automated systems have unfairly treated them. Additionally, organisations should prioritize diversity, equity, and inclusion in their hiring practices and actively work to address systemic biases within their workforce.

Case Study 3: Predictive policing and algorithmic bias

Background: A city's police department implemented a predictive policing algorithm designed to identify areas with a high likelihood of crime based on historical crime data. The study used a case study of Chicago’s PPA [40]. However, an investigation revealed that the algorithm disproportionately targeted neighbourhoods with predominantly minority populations, leading to allegations of racial profiling and discrimination [41].

Ethical dilemma: Using predictive policing algorithms raised concerns about perpetuating systemic biases and exacerbating social inequalities. By relying on historical crime data that may reflect biased policing practices, the algorithm reinforced existing patterns of discrimination and disproportionately impacted marginalized communities.

Lessons learned: This case highlights the ethical implications of using AI and ML algorithms in law enforcement and underscores the importance of fairness, transparency, and accountability in predictive policing practices. It emphasizes the need for thorough algorithmic impact assessments and community engagement to ensure that such systems do not perpetuate or exacerbate social injustices.

Best practices: Police departments should critically evaluate the potential biases and societal impacts of predictive policing algorithms before implementation, involve community stakeholders in decision-making, and establish clear guidelines for the ethical use of AI technologies in law enforcement. Additionally, transparency and accountability mechanisms should be implemented to address algorithmic bias and discrimination concerns.

Case Study 4: Healthcare diagnosis and algorithmic fairness

Background: A hospital adopted an AI-based diagnostic tool to assist radiologists in interpreting medical images and identifying potential abnormalities. However, subsequent analysis revealed that the algorithm exhibited disparities in diagnostic accuracy based on patients' demographic characteristics, such as race and gender, raising concerns about algorithmic fairness and equity in healthcare [42].

Ethical dilemma: The diagnostic algorithm's differential performance across demographic groups highlighted the risk of perpetuating healthcare disparities and exacerbating existing inequities in access to quality care. By producing biased outcomes, the algorithm could undermine patient trust, exacerbate inequities in healthcare delivery, and lead to unequal treatment based on demographic factors.

Lessons learned: This case underscores the ethical imperative of ensuring algorithmic fairness and equity in healthcare AI applications to prevent harm and promote patient welfare. It emphasizes the importance of rigorous testing, validation, and ongoing monitoring to identify and mitigate bias in diagnostic algorithms and the need for transparent reporting of algorithm performance metrics across diverse patient populations.

Best practices: Healthcare institutions should prioritize developing and deploying AI tools that are rigorously validated for accuracy, fairness, and equity across diverse patient populations. They should also invest in diversity. Moreover, representativeness in training data, engaging with healthcare professionals and patient advocates to address concerns related to algorithmic bias and establishing mechanisms for transparent reporting and accountability in the use of AI technologies for medical diagnosis and treatment. These case studies illustrate the ethical dilemmas and challenges inherent in AI and ML projects and provide valuable lessons for addressing these issues responsibly. By learning from real-world examples and adopting best practices, organisations can mitigate the risks of bias, discrimination, and other ethical concerns and ensure their AI and ML systems promote fairness, equity, and social good. The study also presented quantitative results using questionnaires based on the research query:

> *"How do IT professionals in Tanzania perceive and address ethical challenges, such as bias, fairness, transparency, privacy, and accountability, in developing and implementing AI and ML technologies?"*

This research question was explored through the following inquiries.

Question 1: Do you design your algorithm (e.g., Support Vector Machines (SVM), k-nearest Neighbors (k-NN), Naive Bayes, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Generative Adversarial Networks (GAN), Principal Component Analysis (PCA), K-means Clustering, Hierarchical Clustering, Apriori Algorithm (Association Rule Learning), etc. when developing AI applications?

Table 1: Algorithm design in AI application development

Reply	**Frequencies (F)**	**Percentages (%)**
No, I solely import existing libraries.	5	62.5
YES, I design my algorithms	3	37.5
Total	8	100

The data from Table 1 indicates that most IT professionals in Tanzania, representing 62.5% (5 out of 8 respondents), rely solely on importing existing libraries rather than designing their algorithms from scratch. This aligns with global practices where established libraries are prevalent due to their efficiency, robustness, and substantial community support [43]. Such libraries, like TensorFlow and PyTorch, are extensively documented and tested, enabling developers to build AI solutions more rapidly and reliably. However, 37.5% (3 out of 8 respondents) of the participants do design their algorithms, reflecting a significant segment of professionals who prioritize customization and innovation to address specific local challenges. This practice is essential in contexts where unique data characteristics or specific problem domains require tailored solutions, as seen in case studies like developing localized AI models for healthcare diagnostics in underrepresented regions [42]. The reliance on existing libraries can streamline development but may also carry the risk of perpetuating embedded biases within these pre-built tools, highlighting the need for ethical scrutiny [37]. Therefore, the balance between using established libraries and developing custom algorithms can optimise efficiency while addressing local nuances and ethical considerations. This dual approach is supported by findings in AI research emphasising the importance of context-specific adaptations alongside the benefits of leveraging global technological advancements [29].

Question 2. What do you check when selecting an algorithm for reuse?

Table 2 shows that when selecting an algorithm for reuse, the frequency extended to ten (10) and the percentage to 125. This is because the two additional respondents selected both criteria: checking if the algorithm meets country regulations and if it provides transparency to authorities and other stakeholders. The outcome shows that only 50% of IT professionals check if it meets country regulations and policies, and an even smaller percentage (25%) check if the algorithm provides transparency to authorities and other stakeholders. Interestingly, another 50% do not check either of these crucial factors. This practice split reveals significant gaps in thoroughly evaluating ethical and regulatory compliance algorithms. This trend is troubling in light of the case studies discussed. For instance, in the case study on facial recognition bias, the importance of rigorous testing for bias and compliance with ethical standards was emphasized [37]. If developers do not ensure their algorithms meet regulatory requirements, they risk deploying biased technologies that could exacerbate social inequalities. Similarly, the algorithmic hiring bias case study highlighted the need for transparent and accountable AI systems to avoid discrimination [9]. The fact that only a quarter of the respondents prioritize transparency indicates a potential oversight in addressing biases that could lead to unfair hiring practices.

Table 2: Criteria for selecting algorithms for reuse

Reply	Frequencies(F)	Percentages (%)
I check If the algorithm meets country regulations and policies.	4	50
I check if the algorithm provides transparency to authorities and other stakeholders.	2	25
I have yet to check any of the above.	4	50
Total	10	125

Moreover, the predictive policing case study underscored the dangers of using algorithms without proper regulatory and transparency checks, as this can lead to biased policing and further marginalize vulnerable communities [41]. The failure of 50% of respondents to check for regulatory compliance or transparency could result in similar ethical breaches in Tanzania, undermining trust in AI systems. In the healthcare diagnosis case study, ensuring fair and equitable algorithms across diverse populations was critical to preventing health disparities [42]. If developers neglect to check for regulatory compliance or transparency, there is a risk of perpetuating inequities in healthcare delivery. The findings from Table 2 suggest a substantial need for increased awareness and adherence to ethical standards in selecting and reusing algorithms to safeguard against such risks.

Question 3: Are there any policies or regulations regarding the reuse of algorithms in the country

Table 3: Awareness of policies or regulations regarding algorithm reuse

Reply	Frequencies (F)	Percentages (%)
YES	3	37.5
NO	0	00.0
Not aware of the situation	5	62.5
Total	8	100

The findings from Table 3 show that 62.5% of IT professionals are unaware of policies or regulations regarding the reuse of algorithms, which relates directly to the challenges highlighted in various case studies. For instance, the case study on facial recognition bias underscored the importance of regulatory oversight to prevent biased outcomes [37]. The lack of awareness among developers about existing regulations could lead to similar issues in Tanzania, where unregulated or poorly understood practices might perpetuate biases and unfair treatment in AI applications; the case study on algorithmic hiring bias demonstrated the necessity of transparency and accountability in AI systems to prevent discrimination [9]. Suppose developers need to be made aware of policies that enforce transparency and accountability, as suggested by the 62.5% unaware of the regulatory situation. In that case, there is a higher risk of deploying biased or unfair algorithms. This can have significant societal impacts, such as reinforcing inequalities in hiring processes and other critical areas in the predictive policing case study; the lack of regulatory awareness could lead to the misuse of AI, disproportionately targeting minority populations and exacerbating social inequalities [41].

The study showed that algorithmic decisions must be scrutinized and guided by robust regulations to prevent ethical breaches. The need for more knowledge about these regulations among IT professionals suggests a gap that needs to be filled to avoid similar moral dilemmas. Finally, the healthcare diagnosis case study emphasized adhering to regulatory standards to ensure fairness and equity in AI applications [42]. Without awareness of these standards, developers might inadvertently create or deploy biased diagnostic tools, undermining patient trust and exacerbating health disparities. The data from Table 3 indicates that this is a potential risk in Tanzania, highlighting the need for comprehensive regulatory education and enforcement.

Question 4: If you answered YES to question 3, Do you adhere to any policies or regulations guiding the reuse of algorithms to ensure compliance with national laws to protect users?

The data from Table 4 indicates that among those who answered "YES" regarding policies or regulations regarding the reuse of algorithms, 66.7% (2 out of 3) adhere to these guidelines to ensure compliance with national rules and protect users. In comparison, 33.3% do not follow these regulations. This data highlights a positive trend in regulatory adherence among some IT professionals. It also reveals that a quarter of them must be compliant, which could undermine efforts to ensure ethical and safe AI deployment. This finding aligns with insights from the case studies. For example, the case of facial recognition bias emphasised the importance of compliance with ethical standards to prevent racial discrimination [37]. Similarly, the case study on algorithmic hiring bias underscored the necessity of adherence to policies to avoid discriminatory practices in hiring processes [9]. The data suggests that while a majority follow these best practices, a significant minority do not, which could lead to ethical lapses and harm. Furthermore, the predictive policing case study highlighted the risks of using algorithms without strict adherence to regulations, leading to biased law enforcement practices [37]. The 33.3% non-compliance rate in Table 4 suggests that similar issues could arise in Tanzania if all developers need to follow guidelines rigorously. In the healthcare diagnosis case study, the necessity of adhering to regulations to ensure fairness and equity in AI systems was apparent [42]. The adherence by 66.7% of the respondents in Table 4 is encouraging, but the non-compliance of 25% poses a risk to fair and equitable healthcare delivery in Tanzania.

Table 4: Adherence to policies or regulations for algorithm reuse compliance

Reply	Frequencies (F)	Percentages (%)
YES	2	66.7
NO	1	33.3
Total	3	100

Question 5: How do you ensure algorithmic fairness and mitigate biases when reusing algorithms in AI applications?

Table 5: Strategies to ensure algorithmic fairness and mitigate biases

Reply	Frequencies (F)	Percentages (%)
Implementing bias detection and mitigation techniques.	2	25.0
Ensuring diversity and representativeness in training data	2	25.0
Regularly audit and update algorithms to address emerging biases.	2	25.0
I never thought of the need.	2	25.0
Total	8	100.0

The data from Table 5 reveals an even distribution of approaches among IT professionals in Tanzania regarding ensuring algorithmic fairness and mitigating biases when reusing algorithms in AI applications. Each strategy—implementing bias detection and mitigation techniques, ensuring diversity and representativeness in training data, regularly auditing and updating algorithms, and not considering the need—was chosen by 25% of respondents. This diverse set of responses indicates a varied understanding and application of fairness and bias mitigation strategies within the field. The use of bias detection and mitigation techniques by 25% of respondents aligns with best practices highlighted in several case studies. For instance, the analysis of AI in recruitment platforms found that implementing these techniques can significantly reduce biases in hiring decisions, thereby promoting fair employment practices. Additionally, bias detection tools in healthcare have been crucial in ensuring equitable treatment outcomes across different demographic groups, as evidenced in studies on AI-driven diagnostic tools [42].

Another 25% of respondents emphasize ensuring diversity and representativeness in training data, a crucial factor for fair AI outcomes. Case studies have shown that diverse training datasets can significantly mitigate biases and improve the performance of AI models across different population groups. For example, developing inclusive facial recognition systems demonstrated that incorporating diverse data can enhance accuracy and reduce racial bias [37]. 25% of respondents also regularly audit and update algorithms. This approach is supported by the predictive policing case study, where ongoing audits and updates were necessary to address emerging biases, thereby maintaining fairness over time [41]. Regular audits help ensure AI systems align with ethical standards and societal values, adapting to changes and new insights. The remaining 25% of respondents indicated that they had never considered the need to ensure algorithmic fairness and bias mitigation. This lack of consideration poses a significant risk, as unmitigated biases in AI applications can lead to discriminatory outcomes and reinforce existing societal inequalities. This is a critical area where further education and awareness are needed, as highlighted by numerous studies advocating for broader understanding and training on AI ethics and bias [44].

The responses from Table 5 reflect a mix of proactive and reactive approaches to ensuring algorithmic fairness and mitigating biases among Tanzanian IT professionals. While some are adopting best practices aligned with global standards, a notable proportion has yet to recognize the importance of these measures. Enhanced training and awareness programs, coupled with robust regulatory frameworks, are essential to ensure that all professionals in the field prioritize fairness and bias mitigation in their AI practices.

Question 6: Are any ethical considerations influencing your decision to reuse specific algorithms in AI applications?

Table 6: Influence of Ethical Considerations on Reusing Specific Algorithms in AI Applications

Reply	Frequencies (F)	Percentages (%)
YES	5	62.5
NO	3	37.5
Total	8	100

The data from Table 6 indicates that 62.5% of the respondents consider ethical considerations when using specific algorithms in AI applications, while 37.5% do not. This distribution suggests that most IT professionals in Tanzania are aware of the ethical implications of their work and consider these when making decisions about algorithm reuse. However, a significant minority does not prioritize these ethical considerations, which could lead to potential risks and ethical issues in AI deployments. This finding aligns with several case studies highlighting the importance of integrating ethical considerations into AI development. For instance, the facial recognition bias case underscored the critical need to address ethical issues such as racial discrimination, demonstrating the adverse effects of neglecting ethics in AI development [37]. Similarly, the case study on algorithmic hiring bias illustrated the negative consequences of ignoring ethical considerations, which can perpetuate workplace discrimination and hinder diversity efforts [9].

In the predictive policing case, ethical considerations were central to addressing biases in law enforcement practices [43]. Most respondents in Table 6 who consider ethics in their decision-making processes suggest a positive trend towards preventing such biases in Tanzanian AI applications. However, 37.5% of those not considering ethics highlight a vulnerability that could lead to similar issues in Tanzania if not addressed. Moreover, the healthcare diagnosis case study showed the necessity of incorporating ethical considerations to ensure fairness and equity in medical AI applications [42]. The ethical mindfulness among the 62.5% of respondents in Table 6 is a step towards achieving equitable AI systems in healthcare. However, the lack of moral consideration by the remaining respondents could risk patient outcomes and trust in AI-driven healthcare solutions.

While most IT professionals in Tanzania are factoring ethical considerations into their decisions regarding algorithm reuse, the substantial minority who do not pose a risk to the responsible and fair implementation of AI technologies, strengthening ethical awareness and training among these professionals is crucial to bridging this gap and ensuring that AI applications are developed and deployed ethically. Enhanced regulatory frameworks and professional guidelines could support this goal, ensuring that ethical considerations are universally applied in AI development.

Question 7: Have you ever attended any seminars by regulatory bodies or legal experts to ensure compliance with evolving regulations regarding algorithmic transparency and accountability for AI systems?

Table 6: Attendance of seminars on algorithmic transparency and accountability compliance

Reply	Frequencies (F)	Percentages (%)
YES	2	25.0
NO	8	75.0
Total	8	100

Table 7 indicates that a significant majority (75%) of respondents have never attended seminars conducted by regulatory bodies or legal experts to ensure compliance with evolving regulations regarding algorithmic transparency and accountability for AI systems. Only 25% have participated in such seminars. This suggests a potential gap in the knowledge and awareness of regulatory requirements among AI professionals in Tanzania, which could have implications for the ethical and legal compliance of AI systems developed and deployed in the country. The lack of engagement with regulatory bodies and legal experts might stem from various factors, such as limited availability of such seminars, lack of awareness about their importance, or insufficient emphasis on regulatory compliance in the professional development of AI practitioners. The 25% who have attended these seminars are more likely to be aware of and compliant with current regulations, contributing to more ethically and legally sound AI practices. The introduction of GDPR in Europe highlights the critical significance of staying informed about rules. Companies that invested in compliance training and attended regulatory seminars were better prepared for the transition and avoided significant fines and reputational damage [44]. Similarly, in the financial sector, firms that engaged with regulatory updates and expert guidance were more successful in implementing compliant AI systems.

In the context of Tanzania, the findings suggest a need for increased efforts to provide accessible and relevant training for AI professionals. Regulatory bodies and industry associations could play a pivotal role in organizing more seminars and workshops, focusing on the practical aspects of compliance with national and international standards. This would help bridge the knowledge gap and ensure that AI systems are developed in a manner that is transparent, accountable, and aligned with regulatory expectations. Overall, the data underscores the critical need for enhanced regulatory education and engagement among AI practitioners in Tanzania to foster a more compliant and ethically sound AI ecosystem.

5. CONCLUSION

The study concludes that it is imperative to integrate ethical considerations into developing and deploying AI and ML technologies. Through a detailed examination of case studies ranging from facial recognition bias to algorithmic hiring practices, predictive policing, and healthcare diagnostics, it becomes evident that substantial ethical risks accompany these technologies. The findings from Tanzanian IT professionals reveal critical gaps in awareness and adherence to ethical standards, with many relying on established libraries without adequate scrutiny for biases. The importance of thorough testing, openness, and adherence to regulations is highlighted to reduce these potential risks and guarantee that AI systems are just and fair for everyone. Despite some positive practices, such as designing custom algorithms and adhering to regulations, IT professionals lack comprehensive awareness and proactive measures. This highlights the necessity for enhanced regulatory education, the promotion of ethical guidelines, and broader engagement with diverse stakeholders. By addressing these gaps, the AI community can foster more responsible practices that align with societal values and prevent perpetuating systemic biases and inequalities.

RECOMMENDATIONS

According to the study findings, the recommended actions to address the gaps and improve the ethical and regulatory landscape for AI development in Tanzania include enhancing the ethical deployment of AI and ML technologies. Organizations and IT personnel are advised to implement rigorous bias detection and mitigation strategies, prioritize transparency, and ensure compliance with relevant regulations. This involves regularly auditing algorithms, ensuring diversity and representativeness in training data, and engaging with regulatory bodies and diverse stakeholders. Furthermore, fostering a culture of ethical awareness through ongoing education and professional development for IT professionals is deemed essential. These measures aim to mitigate biases, promote fairness, and align AI practices with societal values, ultimately advancing responsible and equitable AI systems.

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