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Deepfake in Kenyan Media Landscape: Assessing Awareness, Detection Capacity, and Training Needs among Communication Practitioners

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Abstract

This study sought to examine deepfake awareness, detection capacity, and training needs among media and communication practitioners in the Kenyan media landscape. The objectives were: to assess the level of awareness of deepfake technology among practitioners; to evaluate their ability to identify deepfakes; to investigate existing training programmes and institutional frameworks aimed at combating deepfakes in Kenyan media houses and communication agencies; and to recommend strategies for capacity building and policy formulation in response to the growing threat of AI-generated misinformation. The study was guided by the Technology Acceptance Model (TAM), which was used to explore awareness, detection capabilities, and training needs related to deepfake technology. Additionally, the Media Literacy Theory (MLT) informed the examination of the skills, knowledge, and attitudes required to critically evaluate media content. A quantitative descriptive survey design was employed to collect data from media and communication practitioners across Kenyan media houses and agencies. Purposive sampling was used to target individuals working in media, public relations, or communication roles, while stratified sampling enabled comparisons across different media platforms, including print, radio, television, and online outlets. Data analysis revealed that a majority of respondents demonstrated low levels of awareness regarding deepfake technology and had limited capacity to detect or respond effectively to such AI-generated content. Furthermore, the findings highlighted a significant gap in professional development, most practitioners reporting a lack of relevant training or institutional support to equip them with the skills and frameworks necessary to address the deepfake challenge. The study recommends that media practitioners undergo mandatory training on deepfake awareness and detection. Additionally, media institutions should develop and

implement clear frameworks and policies to guide the identification and management of AI-generated misinformation.

Keywords: Deepfakes, Media Practitioners, Awareness, Detection Capacity, Training Needs, AI-generated Misinformation, Technology Acceptance Model (TAM)

Introduction

The advent of deepfake technology has created substantial threats to information integrity, public trust, and media credibility globally. The spread of AI-generated misinformation is now a critical distress in regions, such as Africa, particularly due to the recent expansion of digital access, which does not correspond with advancements in media literacy or regulatory preparedness. With catastrophic consequences for areas like Sub-Saharan Africa where digital literacy and legal systems are still in their infancy, the fast-growing deepfake technology has seriously threatened media integrity (Westerlund, 2019). East African countries, including Kenya, are vulnerable to this digital threats, given their limitations in technological infrastructure, policy frameworks, and awareness of emerging trends. In Kenya, public opinion and the advancement of democratic discourse are majorly shaped by the media. However, with its high internet penetration, politically charged information scene, and lack of preparedness to fight AI-generated false information, Kenya is one of the most active media markets on the continent with distinct vulnerabilities in terms of in terms of misinformation, disinformation, and digital security threats (Media Council of Kenya, 2023). Considering the current state of digital threats, it is essential to assess the awareness and capacity of media and communication practitioners to identify and combat deepfakes. Additionally, challenges such as lack of structured training programs, limited institutional preparedness, and unclear policy responses are a concern about the Kenyan media's ability to effectively counter AI-generated misinformation. With the aim of evaluating current awareness levels on deepfake technology amongst Kenyan media and communication practitioners, detection capabilities, and existing institutional measures, the current study is anchored on the listed challenges. Insights from the findings are also used to propose strategic interventions to strengthen Kenya's resilience against deepfake-driven misinformation.

Literature Review

This section provides a review of the theoretical underpinnings, empirical realities, and practical difficulties surrounding deepfake awareness, detection ability, and training demands among media professionals in Kenya. By drawing ideas from important academic works, this review points out weaknesses in present research and proposes future research, policy creation, and practical treatments. The discourse is shaped by three main pillars shape the conversation, namely, theoretical frameworks that assist us to understand media literacy and deepfake acceptance, empirical data on Kenya's current knowledge and detection skills, and noteworthy flaws in contextual, methodological, and conceptual approaches to examining deepfakes in the Kenyan media ecosystem. Therefore, a thorough evaluation of the possibilities and problems related to reducing deepfake threats in Kenya is carried out.

Theoretical Perspectives on Deepfake Adoption and Media Literacy

The Technology Acceptance Model (TAM) was used as a basis to investigate media practitioners' readiness and knowledge to use deepfake detection technologies. The two main elements of the theory regarding new technology adoption are perceived utility and perceived ease of use (Alareeni, Hamdan, & Elgedawy, 2021; Darwish, 2024; Stephanidis & Salvendy, 2024). Practitioners who think detection techniques are helpful and simple to use are more likely to interact with them, according to this model. The results, however, present a contradiction that should be assessed. For instance, even if AI-produced misinformation grows, Kenyan media professionals tend to show poor levels of awareness of and participation with detection tools. This discrepancy begs the question of whether TAM by itself may account for hostility or opposition to deepfake reduction initiatives. Other issues including institutional constraints, a lack of training, and cognitive overload in fast news contexts might further impede adoption. By offering a critical perspective for interpreting how media practitioners and consumers interact with possibly misleading material, the media literacy theory (MLT) complements TAM. Cunliffe-Jones et al. (2021) contend that media literacy entails the development of critical thinking skills, source verification, and awareness of media ecosystems, in addition to technical ability. Low digital literacy and a high degree of social media trust in Kenya make fake news particularly pertinent. Though MLT stresses skill growth, as the research demonstrates, Kenyan media outlets lack organized training courses to apply these ideas in the battle against deepfakes. This mismatch begs the question of whether Western-centric media literacy paradigms can be applied in African settings without major modification. Langmia's (2023) Black Communication Theory can also be used to explain how exploiting already present societal divisions along ethnic, political, and financial lines help disinformation campaigns to disproportionally impact underprivileged groups. Deepfakes can exacerbate conflicts and erode public trust in Kenyan journalism, where ethnic politics are frequently woven into media narratives. Karanja (2023) claims that Kenyan journalists sometimes mistake deepfakes for regular disinformation, which points to a lack of sophisticated understanding of the mechanisms of synthetic media. This theoretical viewpoint exposes a bigger contextual gap in deepfake research because most studies concentrate on Western countries, ignoring the particular socio-political dynamics of African media environments. Efforts to fight deepfakes in Kenya may not succeed without a local understanding of the phenomenon.

Empirical Evidence on Deepfake Awareness and Detection

Empirical research on deepfakes confirms the existence of a worldwide divide in awareness and readiness. Particularly, developing countries like Kenya are adversely impacted. Awodiji and

Owoyemi (2024) draw attention to the presence of sophisticated AI-driven detection tools, including neural network analyzers and blockchain-based verification mechanisms. Financial restrictions, logistical difficulties, and a shortage of technological know-how among media professionals limit their use in Kenya. There is a major capacity gap in detecting deepfakes from other forms of altered content, and this aligns with Karanja's (2023) observation that Kenyan journalists often struggle with this. Many detection devices are already developed in Western settings, where digital literacy, internet bandwidth, and institutional support are stronger, further aggravating this gap. Relying only on such tools might not be practical, given that most newsrooms in Kenya sometimes operate with limited resources. Only 12% of media professionals have been subjected to any official training on detecting changed or fake content, according a thorough study by Cunliffe-Jones et al. (2021) on the literacy of misinformation in Sub-Saharan Africa. The situation is further complicated by the lack of regional training programs. Separately, there have been some success in South Africa, where media outlets and tech companies have partnered to increase detection abilities. Unfortunately, comparable projects in Kenya are rare and underfunded. This contradiction arises from the general differences in technical resource accessibility in Africa, as Mwangi (2023) notes. Economically advanced countries like South Africa and Nigeria spearhead innovation, while others lag behind. Though less focus has been given to the part of traditional media in spreading deepfakes, social media channels already have a well-established function in this. Facebook and WhatsApp are the main channels for deepfakes in Kenya, as Karanja (2023) observes. Meanwhile, Langmia (2023) condemns the nation's overdependence on social media, noting that deepfake abuse might also affect Kenyan radio and television, which are often more dependable than online sources. Most research focuses on digital platforms, yet the critical role broadcast media plays in supporting and legitimizing deepfakes is still little known. Consequently, there is a contextual blind spot that this study sought to address. Given that elderly and rural Kenyans have a high level of faith in traditional media, this divide has important consequences for programs to reduce incorrect information.

Training and Institutional Frameworks: Challenges and Opportunities

Mostly prominent in Kenyan research on deepfake preparedness, is the inadequacy of proper institutional frameworks and training programs. Roe, Perkins, and Furze (2024) call for university curricula in communication and journalism to incorporate deepfake awareness to prepare future practitioners appropriately on the issue. However, Kenyan media education programs tend to remain predominantly outdated since they place more emphasis on traditional reporting conventions than on threats such as intelligence-falsely generated content via the web. While some institutions have begun offering digital security courses, Amatika (2022) notes that the programs are sporadic and underfunded. This insufficiency in training is particularly concerning, considering how rapidly deepfake technology is emerging and necessitates frequent upskilling to keep up with new detection methods.

Since current laws are reactive, rather than preventative, Mwangi (2023) recommends the development of a preemptive institutional and legal framework to combat deepfakes. In Kenya, the Computer Misuse and Cybercrimes Act of 2018 prohibits the dissemination of false information but it makes no particular mention of false media (The National Computer and Cybercrimes Coordination Committee (NC4), 2024). This legal ambiguity makes it challenging for media companies to create clear guidelines for handling deepfakes. The lack of collaboration between government agencies tech firms and news organizations further hinders attempts to develop a logical response. Nonetheless, Kenya could benefit from applying similar cooperative strategies. South Africa has made strides, for example, in establishing multi-stakeholder working groups to combat misinformation. According to studies, research practitioners desire specialized training courses, despite majority of news outlets lacking the funding to support such initiatives. This disparity highlights a larger issue with Kenyan media's resource allocation. Budgetary constraints typically prioritize short-term operational requirements over long-term capacity building. However, some intriguing impromptu projects have emerged. Among other things, workshops on digital validation technology have been made possible by collaboration between regional media outlets and international organizations like UNESCO. Although these efforts are admirable, their long-term impact is limited by their unpredictable nature. Deepfake training in continuing professional development courses is a more environmentally-friendly strategy that is backed by both public and private funding.

Gaps in Current Research and Practice

Given Kenya's unique media landscape, deepfake research is essential. Due to significant differences in legal systems, technological infrastructure, and media consumption habits between Western and African democracies, most existing studies have focused primarily on the context of Western democracies. Since deepfakes in Kenya frequently engage with political and ethnic narratives, specialised responses beyond basic media literacy education are required, according to Langmia (2023). For example, community-based fact-checking initiatives may benefit more from local dialects and cultural contexts than from top-down strategies imported from the Global North. Many studies heavily rely on qualitative surveys, and this runs the risk of bias in understanding deepfake awareness and detection. The reason is that practitioners' unique experiences with synthetic media or their resistance to instruction may be wrongly reported, as the professionals seek to appear informed. Informative data on structural and behavioral constraining factors can be obtained through structured information gathering tools with closed-ended questions. Additionally, many studies conceptually hide significant differences by fusing fabrications with inaccurate information. Majority of the studies are done outside the Kenyan media sector scope, focusing on aspects other than awareness and the capacity of media and communication practitioners to identify and combat deepfakes.

Methods

This section explains the research design that was utilised to collect and analyse data to achieve the study objectives. The target population and sampling techniques are also explained

Research Design

The study adopted a quantitative descriptive research design. Data was collected via an online questionnaire administered through Google Forms, targeting Kenyan media and communication practitioners.

Population and Sampling

The target population comprised individuals working in media, public relations, or communication roles based in Kenya. On the one hand, media and communication practitioners were purposively sampled. On the other hand, practitioners from different media platforms, including print, radio, television, and online outlets were selected using stratified sampling. It was appropriate to adopt the purposive sampling approach it in this study because individuals familiar with the topic or working in relevant fields were targeted. Additionally, stratified sampling enabled comparisons across different media platforms.

Research Instrument

The questionnaire, consisting of close-ended items was used to gather information on media and communication practitioners' awareness, detection ability, training, organizational readiness, and perceived threats related to deepfakes.

Data Analysis Tools

Data was analysed using the statistical Package for the Social Sciences (SPSS). Descriptive statistics frequencies and percentages, cross-tabulations, and where appropriate, Chi-square tests for association were used to explore trends or predictors. The results were presented in figures and tables.

Results and Findings

This section provides the study's findings. Particularly, the demographic characteristics of the informants are presented. Furthermore, results on practitioners' level of awareness of deepfake technology, their ability of these practitioners to identify deepfakes and AI-generated misinformation, the existing training and institutional frameworks available for combating deepfakes in Kenyan media houses or communication agencies, and finally, the recommended strategies for capacity building and policy formulation in response to the threat of AI-generated misinformation.

Demographic Characteristics of the Respondents

A summary of respondents' demographic characteristics is shown in Figure 1.

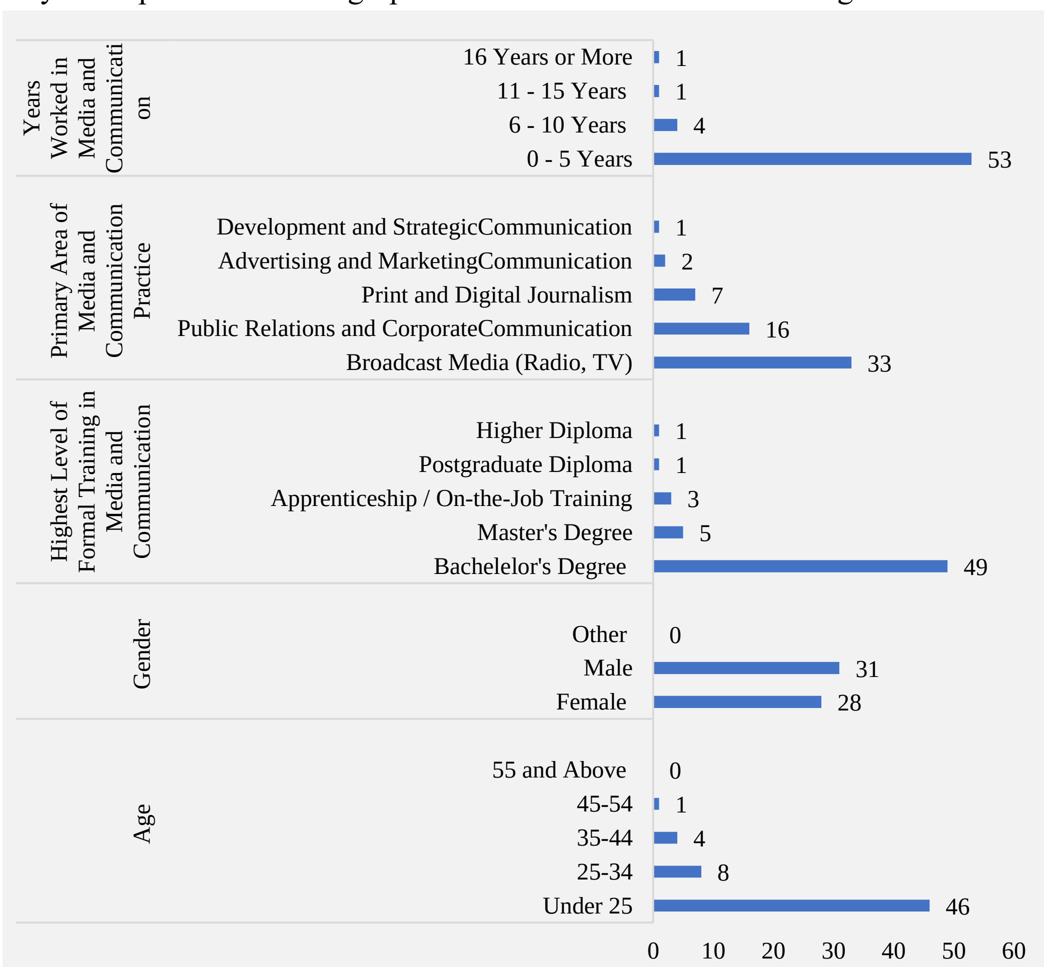

Figure 1: Summary of Respondents' Demographics

As shown in Figure 1, the majority of respondents, 78% were under the age of 25 years. Only a 14% of the informants were in the 25 - 34 years' age bracket, while 7% were aged 35 - 44 years. Only one respondent was in the 45 - 54 years' category and none was over 55. Gender distribution among respondents was relatively balanced, with males, 53%, slightly outnumbering females, 48%. Although the difference is marginal, the near parity suggests inclusive participation. In terms of professional or educational qualifications, an overwhelming 83% of respondents hold a Bachelor's degree in media or communication-related fields. Only a small fraction, 2%, possesses postgraduate qualifications, while 8% have a Master's degree and 2% hold a postgraduate diploma. Additionally, 5% of the informants indicated that they received training through apprenticeships or on-the-job experience, while 2% have a higher diploma. Regarding the respondents' primary area of media and communication practice, those in the broadcast media working in radio or television dominated with 56%. Professionals in the public relations and corporate communication sector followed at 27%. Separately respondents working as print or digital journalists accounted for 12%, while very few informants, 3%, work in advertising and marketing communication or development. Finally, 2% of the respondents in the sample are in strategic communication. It was also found that the majority of respondents, particularly, 90% have five years or less of experience. Only a small minority of the informants, 7%, indicated that they have a work experience of between 6 and 10 years. Finally, respondents with more than a decade of experience represented only 4% of the study sample.

Awareness on Deepfakes Among Kenyan Media and Communication Practitioners

The first objective sought to find out whether or not Kenyan media and communication practitioners are familiar with the concept and risks of deepfakes. Responses on the first question on knowledge on deepfake technology were measured on a scale from 1 = Unaware to 4 = Fully Aware. It was found that most Kenyan media and communication practitioners consider themselves either unaware (67.8%) or moderately aware (18.6%) of deepfake technology.

The relationship between Kenyan media and communication practitioners' awareness of deepfake technology and their deepfake or AI-generated misinformation detection ability was explored using a Chi-Square test for independence. The results are summarised in Tables 4.1 and 4.2.

Table 4.1: Awareness Versus Detection Ability Cross Tabulation

		Detection Ability				Total
		High (Flawless and consistent detection)	Low (Barely noticeable ability)	Moderate (Average detection capability)	None (No ability to detect)	
Awareness	Fully aware	2	1	1	4	**8**
	Moderately aware	0	7	4	0	**11**
	Unaware	4	17	2	17	**40**
Total		**6**	**25**	**7**	**21**	**59**

As per the results in Table 4.1, there were notable differences in detection capabilities across different awareness levels. The frequency statistics showed that only 13.6% of the Kenyan media and communication practitioners are fully aware of deepfakes. Separately, 18.6% are moderately aware, while a significant portion, 67.7% are unaware. Only 25% of the Kenyan media and communication practitioners who are fully aware of deepfakes, indicated that their detection ability is high. However, a significant portion of them, 50.0%, indicated that they have no detection capability. The rest have either low or moderate detection skills. On the other hand, 63.7% of those with moderate awareness demonstrate low detection ability. Separately, 42.5% of the respondents who are unaware of deepfakes have low detection ability, while a similar portion has no detection ability. Only 10% of the practitioners claims high detection levels, while 5% indicate that their deepfake detection ability is only moderate.

Table 4.2: Chi-Square Tests – Awareness Versus Detection Ability

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	17.783[a]	6	.007
Likelihood Ratio	21.174	6	.002
N of Valid Cases	59		

a. 10 cells (83.3%) have expected count less than 5. The minimum expected count is .81.

A significant association between awareness levels and detection ability was found, χ^2 (6) = 17.78, p = .007. The general implication of these results is that Kenyan media and communication practitioners exhibit low levels of awareness on deepfakes.

Training Received on AI and Misinformation Detection

The second objective investigated access to training on AI and misinformation detection, formal or informal, that Kenyan media and communication practitioners have received. A cross-tabulation and a Chi-Square Test were conducted to examine the relationship between employees' level of training access and their AI and misinformation detection abilities. The findings are summarised in Tables 4.3 and 4.4.

Table 4.3: Training Access Versus Detection Ability Cross Tabulation

	Detection Ability				Total
	High (Flawless and	Low (Barely noticeable ability)	Moderate (Average	None (No ability	

		consistent detection)		detection capability)	to detect)	
Training Access	High (Full access)	1	1	0	4	**6**
	Low (Limited access)	1	11	1	5	**18**
	Moderate (Some access)	0	4	2	3	**9**
	None (No access to training)	4	9	4	9	**26**
Total		**6**	**25**	**7**	**21**	**59**

The cross-tabulation results revealed that a significant portion, 44.07%, of the Kenyan media and communication practitioners have no access to training on deepfake detection and management, while 30.51% has low access. Combined, this makes 74.58% of the practitioners that face challenges in accessing training. On the other hand, only 10.17% of the practitioners have high access to training, while 15.25% have moderate access, meaning that only 25.42% can claim they have some access to training. It was further found that the majority of the Kenyan media and communication practitioners with no access to training, particularly 34.6%, exhibited either low or no detection skills. Separately, 61.1% of those with low training access had low detection ability. For the respondents with moderate training access, their detection ability was majorly moderate. Therefore, exposure to training likely correlates with intermediate deepfake detection skill development.

Table 4.4: Chi-Square Tests – Training Access Versus Detection Ability

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	9.400[a]	9	.041
Likelihood Ratio	10.740	9	.029
N of Valid Cases	59		

a. 12 cells (75.0%) have expected count less than 5. The minimum expected count is .61.

The results showed a significant relationship between training access and detection skill, $\chi^2(9) = 9.40$, $p = .041$. Generally, the level of access to relevant training is low, and this influences the practitioners' ability to identify AI-generated misinformation.

Existing Training and Institutional Frameworks for Combating Deepfakes

The third objective focused on an investigation of the existing training and institutional frameworks available for combating deepfakes in Kenyan media houses or communication agencies. In this case, a cross tabulation analysis and Chi-Square test were carried out to find out whether Kenyan media and communication practitioners have access to training and whether this reflects the presence of organizational training on deepfakes management. The results are shown in Tables 4.5 and 4.6.

Table 4.5: Training Access Versus Organizational Training Cross Tabulation

		Organizational Training on Deepfakes Management				Total
		No, and we have no plans yet	No, but we plan to	Yes, occasionally	Yes, regularly	
Training Access	High (Full access)	0	5	1	0	**6**
	Low (Limited access)	6	7	5	0	**18**
	Moderate (Some access)	1	3	3	2	**9**
	None (No access to training)	8	11	7	0	**26**
Total		**15**	**26**	**16**	**2**	**59**

It was found that access to training on deepfake detection and management is generally low amongst Kenyan media and communication Practioners. Similarly, organizational training plans on the same are either minimal or non-existent. Findings further revealed that 44.4% of those without any access to training reported that their organizations also have no training plans in place. Also, 33.3% of respondents with low training access indicated that their organizations have not yet implemented training, although such plans exist. Among those with moderate training access, 33.3% reported occasional organizational training, and 22.2% benefit from regular organizational efforts. In contrast, 83% of the individuals with full access to training are mainly from organizations planning to implement training, though none receives training regularly. These patterns suggest that individual access to training may mirror or depend on broader institutional training efforts.

Table 4.6: Chi-Square - Training Access Versus Organizational Training

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	16.932[a]	9	.050
Likelihood Ratio	14.622	9	.102
N of Valid Cases	59		

a. 12 cells (75.0%) have expected count less than 5. The minimum expected count is .20.

A significant relationship exists between training access and organizational training on deepfakes management, χ^2 (9) = 16.93, p = .050. the implication is that the existence of organizational training on deepfakes predicts media and communication practitioners' access to training.

Handling of Suspected AI-Generated Misinformation by Kenyan Media Organizations

The third objective reviewed how media organisations in Kenya handle suspected AI-generated misinformation. Therefore, the focus was on whether the media institutions have strategies or frameworks in place to deal with deepfakes and AI-generated misinformation. It was also reviewed whether or not the organizations have conducted training or workshops and how this correlates with practitioners' confidence in their ability to verify suspicious content. The results are summarized in Figure 4.2 and Tables 4.7 and 4.8.

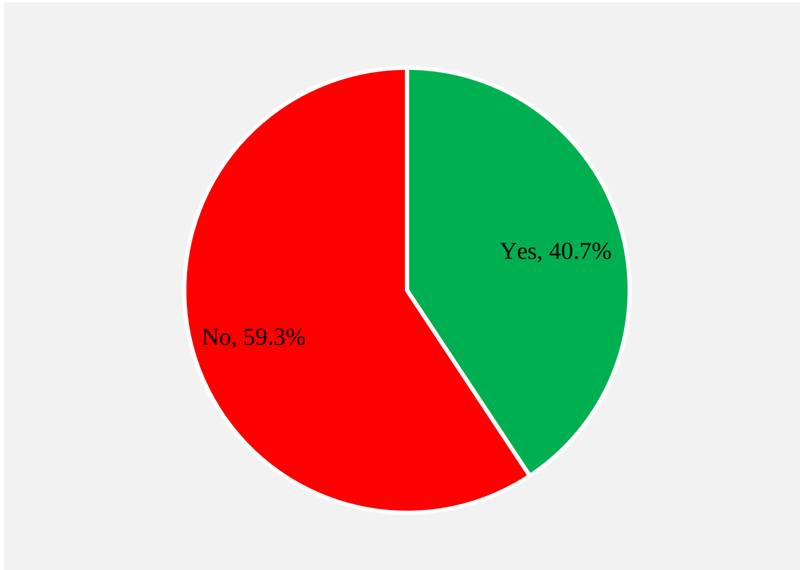

Figure 4.2: Existence of Deepfake Management Strategies

As shown in figure 4.2, majority of the media organizations, 59.3%, have not implemented strategies to deal with deepfakes. Only 40.7% have frameworks that practitioners can utilize in handling deepfakes and AI-generated misinformation.

Table 4.7: Existence of Deepfakes Management Strategy and Verification Confidence

		Deepfakes Verification Ability Confidence				Total
		Moderately confident	Not confident at all	Slightly confident	Very confident	
Deepfakes Management Organizational Strategy	No	6	15	7	7	**35**
	Yes	4	14	5	1	**24**
Total		**10**	**29**	**12**	**8**	**59**

It was found that in organizations without deepfake management strategies, 25.4% of the practitioners are not confident they can verify deepfakes, while 11.9% only have minimal confidence on the same. Interestingly, even in organization with strategies, the lack of confidence is exhibited by 23.7% of the practitioners. Only 8.5% of the practitioners from organizations with existing frameworks can confidently identify and verify deepfakes.

Table: 4.8: Training on Deepfakes Management and Verification Ability Confidence

		Deepfakes Verification Ability Confidence				Total
		Moderately confident	Not confident at all	Slightly confident	Very confident	
Organizational Training on Deepfakes Management	No, and we have no plans yet	3	5	4	3	**15**
	No, but we plan to	5	13	5	3	**26**
	Yes, occasionally	2	9	3	2	**16**
	Yes, regularly	0	2	0	0	**2**
Total		**10**	**29**	**12**	**8**	**59**

It was found that the majority of practitioners from organizations without training strategies on deepfake management, 45.8%, do not exhibit any identification and verification ability. Only 23.7% of such practitioners have confidence in their ability to verify deepfakes. Despite some institutions having training programs, 28.6% of practitioners from such firms are not confident of their ability to verify deepfakes, while only 6.8% are confident of their abilities.

Support and Interventions Needed to Combat Deepfakes

The fourth objective of the study focused on the support or interventions that practitioners believe are necessary to combat deepfakes effectively. Figure 4.3 provides a summary of the suggested support and interventions that can help combat deepfakes.

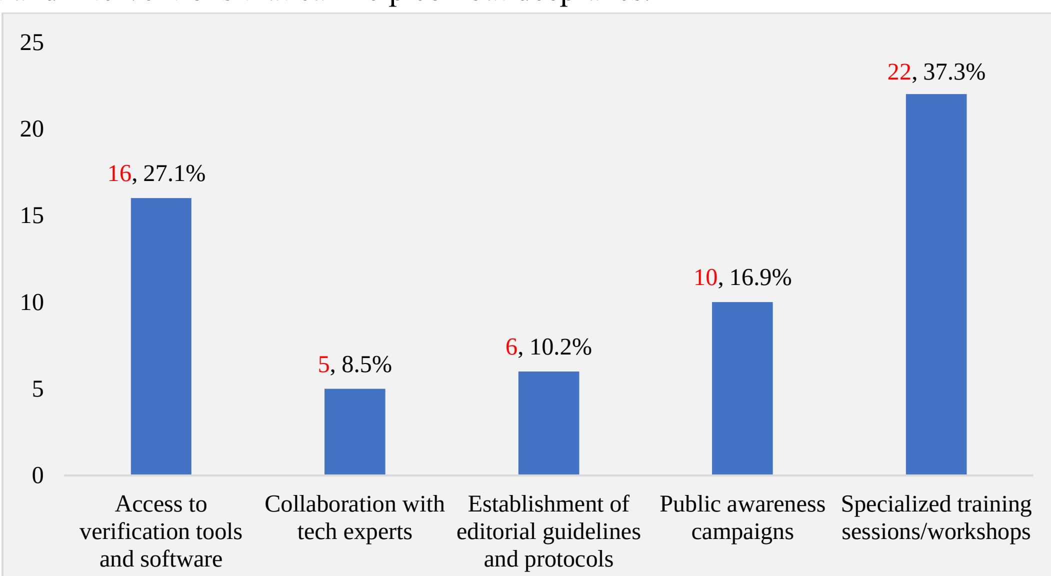

Figure 4.3: Support and Interventions for Combating Deepfakes

Based on the results, the provision of specialized training sessions or workshops was the most frequently cited intervention, with 22 practitioners (37.3%) identifying it as a critical need. Additionally, 16 respondents (27.1%) emphasize the need for access to verification tools and software. Other recommended interventions are public awareness campaigns (16.9%), the establishment of editorial guidelines and protocols (10.2%), and finally, collaboration with tech experts (8.5%).

Discussion

The study established that there is a gap in the awareness and preparedness of Kenyan media and communication practitioners in addressing the challenges posed by deepfakes and AI-generated misinformation. The results concur with those of Awodiji and Owoyemi (2024), who found that the level of awareness of deepfake technology and the readiness of media and communication practitioners to deal with it are low in Africa, particularly Kenya, which is adversely affected. The findings further support the assertion by Karanja (2023) that Kenyan journalists face challenges in differentiating deepfakes from altered content or reality. Therefore, the level of awareness of deepfake technology among Kenyan media and communication practitioners is still low. A majority of practitioners still lack both awareness and detection ability, with only a small fraction demonstrating high competence in identifying manipulated content. Sensitization programs may help address this challenge to improve the credibility of journalism in the country.

It was also found that Kenyan media and communication practitioners have limited access to relevant training. The problem is exacerbated by inadequate institutional support since most media organizations do not have elaborate structured training programs or comprehensive strategies to combat deepfakes. Despite the study's findings that the presence of organizational frameworks and training efforts significantly influences practitioners' skills and confidence levels, it was noted that such initiatives remain sparse or inconsistent in the Kenyan media and communication context. The findings are in agreement with those of Cunliffe-Jones et al. (2021) that only a few media professionals within the Sub-Saharan region in Africa have undergone official training on the detection of fake or altered content. As previously noted by Mwangi (2023), resource accessibility could be the main reason behind the current situation. Another cause of this challenge that had been identified by Amatika (2022) is the infrequency and insufficient funding of training programs.

Insufficiency in the existing institutional frameworks for combating deepfakes in Kenyan media houses or communication agencies was also established. The majority of the practitioners indicated that their organizations do not have deepfake management strategies. Consequently, they have not been trained on the identification and management of AI-generated misinformation, and in case of any familiarization, the engagement levels are minimal. As a result, the verification ability of deepfakes among most of the media and communication practitioners remains low. The findings affirm the need for specialized media literacy education, as suggested by Langmia (2023). Similarly, as noted by Mwangi (2023), the development of a preemptive institutional and legal framework to combat deepfakes is necessary in the Kenyan media industry. Therefore, practical solutions to the current challenges are required.

Conclusion and Recommendations

In sum, the study's research questions were sufficiently answered through empirical analysis. It was revealed that most Kenyan media and communication practitioners have low awareness and limited ability to detect deepfakes. Moreover, only a few of them have received relevant training. Lack of institutional support and structured strategies to address AI-generated misinformation across most of the media organizations was also noted. In light of the study results, systematic investment in training, institutional capacity building, and policy development are necessary to equip media professionals with appropriate tools, as this would help strengthen media credibility and safeguard information integrity in this era that is characterized by advanced AI technologies. Organizational frameworks should be tailored to support deepfake identification and management while frequently upskilling media and communication professionals to keep up with new detection methods. It is further recommended that university curricula in communication and journalism should incorporate deepfake awareness to prepare future practitioners appropriately on the issue. Preemptive institutional and legal frameworks that entail partnerships with industry experts would also help to combat deepfakes if implemented correctly.

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Conflict of Interest Statement

The authors declare that there is no conflict of intertest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Licensing Statement

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