INFLUENCE OF DEEPFAKES ON THE AUDIENCE'S BELIEVABILITY OF BROADCAST MEDIA CONTENTS

AMUNE Philip Asusheyi PhD
Department of Mass Communication
University of Nigeria, Nsukka
amunephilip@gmail.comNjoku,

KANU Okechukwu Stanley
Department of Mass Communication
ESUT Business School
oknk2014@gmail.com

Abstract

This study investigated the influence of deepfake technology on the believability of broadcast media online content among residents of Enugu Urban, Nigeria. Employing a descriptive survey research design, data were collected from 456 respondents across Enugu East, Enugu North, and Enugu South local government areas using structured questionnaires. The study was grounded in Media Dependency Theory and examined four key dimensions: awareness levels of deepfake technology, the impact of deepfakes on media credibility perceptions, demographic influences on susceptibility, and coping strategies employed by audiences. Findings revealed that 85.5% of respondents demonstrated awareness of deepfake technology, with social media serving as the primary source of information (76.4%). However, only 38.6% expressed confidence in their ability to identify deepfakes, indicating a significant awareness-competence gap. The study established a significant negative correlation ($r = -0.482$, $p < 0.05$) between deepfake awareness and perceived media credibility, with 79% of respondents reporting reduced trust in online broadcast media. Age emerged as a significant factor influencing susceptibility, with older respondents (56+ years) showing vulnerability scores 26% higher than younger cohorts (18-25 years). Educational attainment demonstrated a protective effect, with postgraduate degree holders showing 20% lower susceptibility compared to those with secondary education. Gender differences in susceptibility were statistically insignificant. Regarding verification practices, source credibility checking was the most commonly employed strategy (58.8%), while formal fact-checking resources remained underutilized (18.9% frequent use). Rather than abandoning online media consumption, 62.7% of respondents reported maintaining engagement while exercising heightened skepticism. The study concludes that deepfake technology has precipitated a credibility crisis for broadcast media content in urban Nigeria, cultivating generalized skepticism that threatens democratic discourse and civic engagement. Recommendations include implementing content authentication systems, integrating comprehensive media literacy education, establishing regulatory frameworks, and developing accessible fact-checking infrastructure.

Keywords: Deepfakes, Media Credibility, Broadcast media, Misinformation, Digital literacy, Nigeria, Media Dependency Theory

INTRODUCTION

The digital revolution has fundamentally transformed the creation, dissemination, and consumption of information worldwide. In the current media landscape, audiences are constantly inundated with an overwhelming volume of content through various broadcast, digital, and social media platforms. While this transformation has democratized access to information, it has also brought about significant challenges related to media credibility and audience trust. One of the most critical technological developments that threatens the integrity of broadcast media content is the emergence of deepfake technology.

Deepfakes represent a convergence of advanced technologies, such as artificial intelligence (AI), machine learning, and computer vision, which enable the creation of hyper-realistic synthetic media content (Chesney & Citron, 2019). The term "deepfake" first emerged in 2017 when a Reddit user coined it to describe pornographic content featuring manipulated images of celebrities' faces superimposed onto other individuals' bodies (Moriarty, 2018). Since then, deepfake technology has evolved at a rapid pace, enabling the production of hyper-realistic audio and video content that poses substantial risks for misinformation, digital manipulation, and the erosion of public trust in media institutions (Maras & Alexandrou, 2019). Deepfakes are now a significant tool for spreading misinformation, as they can be used to create fabricated videos and audio recordings that appear highly convincing, even to the most discerning viewers (Franke & Metzger, 2020).

The proliferation of deepfakes has been accelerated by the widespread accessibility of artificial intelligence tools and sophisticated software to the general public. What once required professional studios, advanced technical skills, and substantial resources can now be done with consumer-grade hardware and readily available, often free, applications (Gretton et al., 2020). This democratization of technology has led to an exponential increase in the creation and distribution of deepfake content. In fact, researchers have documented a 300% increase in the number of deepfakes between October 2019 and June 2020 alone (Yin, 2021). As a result, deepfakes have become a major concern for media credibility, as distinguishing between real and fabricated content has become increasingly difficult.

In the context of Nigeria, Africa's most populous democracy, the implications of deepfakes are particularly significant. With its high rate of social media penetration, combined with relatively low digital literacy in certain segments of the population, Nigeria is highly vulnerable to the spread of manipulated media content (Adeosun et al., 2020). The country has also experienced political instability, which has made it a prime target for the use of deepfake technology to influence public opinion and electoral processes. During the 2023 Nigerian general elections, deepfakes emerged as a significant concern, with manipulated videos and audio clips of politicians circulating widely on social media platforms. These deepfake videos included fabricated voice recordings of political figures allegedly discussing election rigging, as well as deepfake content of international figures purportedly endorsing specific candidates (Nwabueze, 2023). Such instances highlight the growing risks posed by deepfakes in the context of Nigerian politics, particularly in an era where the public relies increasingly on digital media for news and information.

Enugu Urban, a metropolitan center in southeastern Nigeria, serves as an important case study for understanding how urban residents perceive and respond to deepfake content in broadcast media. With an estimated population of approximately 876,000 in 2024 (National Population Commission, 2024), Enugu Urban is home to a diverse demographic, including educated professionals, students, and civil servants. As a vibrant urban center with a high level of media consumption, residents of Enugu are exposed to both traditional broadcast media and digital platforms, including social media, where deepfake content is often disseminated. This unique demographic offers an ideal context for exploring how urban populations evaluate the credibility of online broadcast content in an age where deepfake technology challenges the authenticity of information (Sundar et al., 2017).

The rise of deepfake technology raises fundamental questions about the future of public discourse, democratic participation, and societal trust. As synthetic media becomes increasingly difficult to distinguish from authentic content, audiences face growing challenges in discerning what is real and what is fabricated. This uncertainty poses a threat to the integrity of media institutions, which are traditionally relied upon to provide accurate and reliable information. Therefore, understanding how residents of Enugu Urban assess the believability of online broadcast content, particularly in the context of deepfake technology, is crucial for informing media literacy initiatives and policy responses aimed at combating misinformation in the digital age. This study seeks to contribute to the growing body of knowledge on media credibility, with a focus on how deepfakes influence public perceptions of the authenticity of broadcast media content in Nigeria.

Statement of the Problem

In Nigeria, the problem is particularly acute given the country's history of election-related misinformation and the critical role of media in democratic processes. During the 2023 elections, deepfakes were deployed as tools for political mudslinging, character assassination, and the manipulation of public perception. Research has documented that these manipulated contents, primarily in picture and voice forms, were used predominantly for negative purposes, including defaming political figures and presenting certain personalities as unfit for leadership positions.

The challenge is compounded by several factors specific to the Nigerian context. First, there is limited awareness among the general public about deepfake technology and its capabilities. Many voters can identify simple photo manipulations, but deepfakes, AI-generated audio, and hyper-realistic images are considerably more difficult to detect. Second, there is a high cultural trust in visual and audio evidence, making Nigerian audiences particularly vulnerable to deepfake manipulation. Third, fact-checking infrastructure and resources remain underdeveloped compared to Western contexts, limiting the capacity for rapid debunking of manipulated content.

Furthermore, the psychological impact of deepfakes extends beyond individual instances of deception. Research has demonstrated that exposure to deepfakes increases uncertainty and reduces trust in news media generally, potentially contributing to a broader erosion of civic engagement and democratic participation. This phenomenon, sometimes termed the "liar's dividend," allows bad actors to dismiss authentic evidence as fabricated, further muddying the information environment.

Despite the growing significance of this issue, there is a notable gap in empirical research examining how Nigerian urban populations perceive and respond to deepfake content in broadcast media. Most existing studies on deepfakes have been conducted in Western contexts, with limited attention to how these dynamics play out in African societies with distinct media ecosystems, cultural contexts, and levels of digital literacy. This study addresses this gap by investigating the influence of deepfakes on the believability of broadcast media online content among Enugu Urban residents.

Research Questions

The following research questions are addressed in this study:

1. What is the level of awareness of deepfake technology among residents of Enugu Urban?
2. How does exposure to deepfake content influence the credibility perception of broadcast media among Enugu Urban residents?
3. What is the relationship between demographic characteristics (age, education, gender) and susceptibility to deepfake-influenced media content among Enugu Urban residents?
4. What coping strategies do Enugu Urban residents employ in evaluating the authenticity of broadcast media content online?

Scope of the Study

This study is delimited to examining the influence of deepfakes on the believability of broadcast media online content among residents of Enugu Urban, comprising the three local government areas of Enugu East, Enugu North, and Enugu South. The study focuses on adult residents aged 18 years and above who have access to the internet and consume broadcast media content online. The geographical scope is limited to the Enugu Urban metropolis, and findings may not be generalizable to rural populations or other urban centers in Nigeria.

The content scope encompasses deepfake content related to broadcast media, including manipulated video and audio content of public figures, news personalities, and political actors that circulates on online platforms. The study examines both awareness of deepfakes and their influence on audience perception of media credibility, without extending to technical detection methods or policy analysis.

The temporal scope covers the period of data collection in 2025, with references to deepfake incidents and media events occurring primarily between 2020 and 2025.

LITERATURE REVIEW

The Meaning of Deepfakes

Deepfakes constitute a category of synthetic media generated through sophisticated artificial intelligence algorithms, primarily deep learning techniques. The term combines "deep learning" and "fake," reflecting the technological foundation of this media manipulation method. Deepfakes are defined as highly realistic synthetic media generated by algorithms that can create convincing digital representations of real individuals without their consent or knowledge.

The technology fundamentally relies on neural networks trained on extensive datasets to learn patterns that enable the imitation of real individuals and the synthesis of fictional ones. Unlike traditional image or video manipulation techniques that require substantial manual effort and expertise, deepfake technology automates much of the process, allowing for the creation of realistic forgeries with minimal human intervention. This automation has significantly lowered the barriers to creating sophisticated media manipulations.

Academic research on deepfakes is bifurcated between the field of computer vision, which focuses on developing techniques for both creating and detecting deepfakes, and the humanities and social sciences, which examine the social, ethical, and informational implications of the technology. This interdisciplinary attention reflects the multifaceted nature of deepfakes as both a technical phenomenon and a social concern.

The definition of deepfakes remains contested in academic literature, with no universal consensus on the precise boundaries between deepfakes and other forms of media manipulation. Some scholars adopt an inclusive approach, encompassing all forms of AI-generated or AI-manipulated media, while others restrict the term to specific techniques involving deep neural networks. For the purposes of this study, deepfakes are understood as media content—whether video, audio, or images—that has been artificially generated or significantly manipulated using deep learning technologies to misrepresent reality.

Relationship Between Deepfakes and Computer Vision

Computer vision, a subfield of artificial intelligence, provides the technological foundation for both the creation and detection of deepfakes. The relationship between these domains is symbiotic: advances in computer vision enable more sophisticated deepfake creation, while simultaneously providing tools for their detection.

The creation of deepfakes primarily relies on two computer vision architectures: autoencoders and Generative Adversarial Networks (GANs). Autoencoders function by compressing facial features into a latent representation and then reconstructing them, allowing for face swapping when different decoders are applied to encoded features. The process involves training a shared encoder on images of two different faces, with separate decoders learning to reconstruct each face's specific features. During synthesis, the encoder extracts features from one face while the decoder trained on another face generates the output, effectively transferring facial characteristics.

GANs represent a more sophisticated approach, comprising two competing neural networks: a generator that creates synthetic content and a discriminator that attempts to distinguish real from fake. Through iterative training, the generator becomes increasingly proficient at producing realistic content that can fool the discriminator. This adversarial process has yielded remarkable improvements in the quality of synthetic media, with some deepfakes now achieving near-photorealistic quality.

Detection methods similarly leverage computer vision techniques, employing convolutional neural networks (CNNs) to identify artifacts and inconsistencies in manipulated media. These detection systems analyze features such as facial inconsistencies, unnatural blinking patterns, lighting anomalies, and compression artifacts. Research has achieved detection accuracy rates exceeding 97% under controlled conditions, though performance degrades significantly when encountering novel deepfake generation methods or heavily compressed content.

The relationship between deepfakes and computer vision exemplifies a technological arms race, where improvements in generation capabilities drive advances in detection methods, which in turn spur more sophisticated generation techniques. This dynamic has significant implications for media authenticity, as detection capabilities consistently lag behind generation methods.

Types of Deepfake Content

Deepfake technology manifests in several distinct forms, each with unique characteristics and implications for media credibility:

Face-Swap Deepfakes: The most prevalent form of deepfakes involves replacing one person's face with another in video content. This technique uses facial recognition algorithms to map the facial features of both source and target individuals, enabling seamless transformation that maintains natural expressions and movements. Face-swapping can range from obviously artificial memes to highly convincing manipulations capable of deceiving trained observers.

Voice Cloning Deepfakes: Audio deepfakes replicate an individual's voice through text-to-speech synthesis or voice conversion algorithms. These systems analyze vocal characteristics including pitch, tone, accent, and speaking patterns to generate synthetic speech that closely resembles the target individual. Voice cloning has been employed in financial fraud schemes, with documented cases of scammers impersonating executives to direct unauthorized transfers of hundreds of thousands of dollars.

Lip-Sync Deepfakes: These manipulations modify mouth movements to match new audio content, creating the appearance that someone spoke words they never actually said. Lip-sync deepfakes are particularly concerning for their potential to fabricate political speeches, interviews, or confessions.

Full-Body Reenactment: Advanced deepfake techniques can capture and transfer entire body movements and gestures from one individual to another. This enables the creation of content showing targets performing actions they never executed, with applications ranging from entertainment to potentially fabricating alibi videos or staged evidence.

Talking Head Generation: This approach generates new video frames from a single reference image, animating still photographs to create realistic talking videos. Such technology requires only a photograph to create convincing video content, significantly expanding the potential targets of deepfake manipulation.

Each type presents distinct detection challenges and potential harms, with audio-video combinations representing the most challenging detection scenarios due to the need to verify multiple modalities simultaneously.

Influence of Deepfakes on Fake News

The relationship between deepfakes and fake news represents one of the most significant threats to information integrity in the contemporary media ecosystem. Deepfakes provide a powerful tool for creating and disseminating false information, amplifying the reach and impact of misinformation campaigns.

Deepfakes enhance the persuasive power of disinformation by providing visual and auditory evidence that appears to corroborate false claims. The psychological impact of video evidence is substantial; audiences tend to place higher trust in audiovisual content compared to text-based information. This phenomenon, rooted in the cultural assumption that "seeing is believing," makes deepfakes particularly effective vehicles for spreading misinformation.

Research has demonstrated that deepfakes contribute to what scholars term "information disorder" through multiple mechanisms. First, they enable the creation of entirely fabricated events—speeches never given, meetings never held, actions never taken. Second, they facilitate the manipulation of authentic events through subtle alterations that change meaning while maintaining apparent authenticity. Third, and perhaps most insidiously, the mere existence of deepfake technology creates a "liar's dividend" that allows individuals to dismiss authentic evidence as potentially fabricated.

The relationship between deepfakes and fake news is particularly concerning in political contexts. Studies have documented the use of deepfakes in election campaigns globally, including fabricated endorsements, manipulated speeches, and false representations of candidates. In

Nigeria's 2023 elections, deepfakes were deployed for political propaganda and character assassination, with manipulated audio recordings suggesting election rigging and fake videos purporting to show international endorsements of candidates.

The viral spread of misinformation through social media exacerbates the impact of deepfakes. Content spreads rapidly through networks before fact-checkers can respond, and corrections often fail to reach all exposed individuals. Research indicates that false information spreads faster and reaches more people than corrections, creating lasting effects on public perception even after debunking.

Audience and Deepfakes

The interaction between audiences and deepfake content involves complex psychological and social dynamics that shape perception, belief, and behavior. Understanding these dynamics is crucial for assessing the impact of deepfakes on media credibility.

Research consistently demonstrates that humans perform poorly at detecting deepfakes. Studies indicate that detection accuracy among untrained individuals rarely exceeds chance levels, with many participants unable to distinguish between authentic and synthetic content. This vulnerability is exacerbated by the rapid improvement in deepfake quality, which increasingly eliminates the visual and auditory artifacts that once betrayed manipulation.

Several factors influence audience susceptibility to deepfakes. Confirmation bias plays a significant role: individuals are more likely to accept deepfakes that align with their preexisting beliefs and more skeptical of content that contradicts them. Political orientation, in particular, shapes responses to political deepfakes, with partisans more readily believing manipulated content that supports their preferred narrative.

Digital literacy moderates deepfake susceptibility, though the relationship is complex. Education about deepfake technology and detection strategies can improve identification rates, but some research suggests that awareness campaigns may have the unintended consequence of increasing general skepticism toward all media content, including authentic material. This "prebunking paradox" represents a significant challenge for media literacy interventions.

Demographic factors also influence deepfake vulnerability. Age emerges as a significant risk factor, with older individuals showing higher susceptibility to deepfakes in some studies. Educational attainment appears to provide some protection, with higher education levels associated with reduced susceptibility. However, these relationships are not universal and may vary across cultural contexts.

The psychological impact of deepfake exposure extends beyond individual deception to broader effects on media trust. Experimental research has shown that watching deepfake videos reduces overall trust in news media, even when participants are subsequently informed of the manipulation. This erosion of trust may contribute to declining civic engagement and democratic participation, as citizens become unable or unwilling to distinguish fact from fiction.

Empirical Review

Empirical research on deepfakes and media credibility has expanded significantly in recent years, though studies specific to African contexts remain limited. This section reviews relevant empirical studies that inform the current research.

Vaccari and Chadwick (2020) conducted a seminal experimental study examining the effects of deepfake exposure on trust in news media. Their research exposed 2,005 participants to different versions of a deepfake video featuring Barack Obama and Jordan Peele, with conditions varying in the degree of deception. Results demonstrated that exposure to deceptive deepfakes increased uncertainty about the authenticity of media content generally and reduced trust in news on social media platforms. Importantly, this effect persisted even after participants were informed about the manipulation, suggesting lasting impacts on media credibility perceptions.

Ekpang, Iyorza, and Ekpang (2023) investigated perspectives on deepfake use during Nigeria's 2023 general elections, surveying 1,123 respondents across five states in the South-South region. Their findings revealed extensive use of deepfakes during the election period, primarily in picture and voice forms. The study documented that deepfakes were employed as mudslinging tools to damage politicians' images and as propaganda instruments to present certain figures as unfit for leadership. This research provides important context for understanding deepfake deployment in the Nigerian electoral environment.

Ahmed (2021) explored the relationship between deepfake sharing and news skepticism through survey research. The study found that inadvertent sharing of deepfake content was associated with increased skepticism toward news media generally, supporting theoretical predictions about the broader effects of deepfake exposure on media trust. The research highlighted the role of cognitive ability as a moderating factor, with higher cognitive ability associated with more nuanced responses to deepfake exposure.

A recent scoping review by researchers at the University of KwaZulu-Natal examined 22 empirical studies on deepfake effects, finding that early research has often produced inconclusive results regarding the unique persuasive effects of deepfakes. The review noted significant methodological limitations in existing studies, including poor use of comparison conditions and low-quality deepfake stimuli. The authors concluded that speculation about deepfake harms has substantially outpaced empirical evidence.

Research examining deepfakes in the Global South remains sparse but growing. A study exploring deepfake impacts in developing societies found that 91.8% of respondents expressed concern about the potential for deepfakes to manipulate public perception. The research highlighted distinctive challenges in these contexts, including limited fact-checking resources and lower digital literacy levels, which may amplify deepfake impacts.

Experimental research from India examined how deepfake exposure affects news accuracy perceptions in a non-Western context with relatively low digital literacy. The study found that participants exposed to malicious deepfakes subsequently rated related news content as less accurate, even when the news itself was authentic. Notably, cognitive ability did not moderate this effect, suggesting that education alone may not protect against deepfake-induced skepticism.

Theoretical Framework

For a study exploring the impact of deepfake technology on media credibility and audience perceptions, particularly in a context like Enugu Urban, Nigeria, **The Elaboration Likelihood Model (ELM)** and **Media Dependency Theory** are two suitable theoretical frameworks. However, given the focus on media credibility, trust, and how individuals process information in a digital media age, **Media Dependency Theory (MDT)** is likely the most appropriate.

Media Dependency Theory (MDT)

Media Dependency Theory, first proposed by Sandra Ball-Rokeach and Melvin DeFleur (1976), suggests that individuals' dependence on media for information, entertainment, and socialization increases as the media plays a more central role in their lives. In a context where deepfakes challenge the credibility of media, MDT helps to explain how people rely on media sources for trustworthiness, particularly when new technological tools (like deepfakes) alter the authenticity of content.

Why MDT Is Suitable for This Study*:*

1. **Audience Trust and Dependency**: According to MDT, the more dependent individuals are on media for fulfilling their informational needs, the more likely they are to believe and trust what the media presents (Ball-Rokeach & DeFleur, 1976). In the case of deepfakes, this theory could be used to investigate whether, despite the rise of synthetic media, audiences in Enugu Urban continue to rely on broadcast media or whether they become more critical of the content they consume.
2. **Credibility of Media**: Media Dependency Theory suggests that people's perception of media credibility influences their trust and reliance on media messages. In an era where deepfakes are becoming more prevalent, it would be insightful to explore whether Nigerians in Enugu Urban have changed their perceptions of traditional and digital media sources' credibility due to the increasing exposure to manipulated content (Ball-Rokeach & DeFleur, 1976; Hasebrink, 2008).
3. **Social and Cultural Context**: The social environment plays a critical role in shaping media dependency. As Nigeria's media ecosystem interacts with various cultural, political, and social factors, the theory helps contextualize how individuals, especially in urban environments like Enugu, interact with media in ways that either bolster or erode trust in both traditional and online sources of information (Kiousis, 2001). Understanding the level of dependency people have on different media channels can inform how deepfakes might alter the public's media consumption behavior and trust.

4. **Role of Digital Media**: The rise of social media and digital platforms in Nigeria, where deepfake content is widely circulated, underscores the growing role of these platforms in shaping perceptions. According to MDT, as media exposure increases and individuals become more dependent on digital platforms for information, they may be more susceptible to the influence of manipulated media content (Jang & Kim, 2020).
5. **Impact of Misinformation**: MDT also speaks to how media content that is perceived as unreliable or deceptive (like deepfakes) can affect the relationship between individuals and media. In this study, the focus could be on how deepfakes impact the level of dependency Nigerians in Enugu Urban place on broadcast media versus social media, considering the increasing role of misinformation in shaping public perceptions.

Media Dependency Theory and Deepfakes

In this study, MDT could be used to explore the following key questions:

- To what extent are residents of Enugu Urban dependent on broadcast media (traditional vs. digital) for their news and information?
- How does the growing prevalence of deepfakes affect their trust in these media sources?
- Are residents more likely to question the authenticity of media content they consume as the volume of deepfakes increases?
- Does the dependence on certain media types (e.g., social media platforms vs. broadcast news) increase the likelihood of falling victim to deepfake content?

By exploring these aspects, MDT provides a comprehensive framework for understanding how deepfakes challenge media trust and credibility, especially in regions like Enugu Urban, where there is significant engagement with both traditional and digital media channels

RESEARCH METHODOLOGY

Research Design

This study employs a descriptive survey research design to investigate the influence of deepfakes on the believability of broadcast media online content among residents of Enugu Urban. The survey design is appropriate for this study because it allows for the systematic collection of data from a representative sample of the population, enabling generalization of findings to the broader population of Enugu Urban residents (Odionye, Anorue, and Ekwe, 2024).

The descriptive approach facilitates the examination of relationships between variables without manipulation, providing insights into naturally occurring phenomena. The cross-sectional nature of the survey allows for efficient data collection at a single point in time while capturing variations across demographic groups.

Population of the Study

The population for this study comprises adult residents of Enugu Urban aged 18 years and above who have access to the internet and consume broadcast media content online. Enugu Urban encompasses the three local government areas of Enugu East, Enugu North, and Enugu South.

According to population estimates, the Enugu metropolitan area has a population of approximately 876,000 residents as of 2024. This figure represents the urban agglomeration including the core city and adjacent suburban areas. The city has experienced steady population growth, with an annual growth rate of approximately 3.4% in recent years.

For the purposes of this study, the target population is further refined to include only adult residents (18 years and above) with internet access who consume online broadcast media content. Based on national statistics indicating approximately 55% urban internet penetration in Nigeria and census data on adult population proportions, the estimated target population for this study is approximately 400,000 eligible residents across the three local government areas (Ngwu, and Ekwe, 2015).

Sample Size Determination

The sample size of 400 was determined using the Taro Yamane formula from populations of 876,000 residents. The formula is expressed as:

$$n = N / [1 + N(e)^2]$$

Rounding up, the minimum required sample size is **400 respondents**. To account for potential non-response and incomplete questionnaires, the study will oversample by 20%, targeting **480 respondents** for questionnaire distribution.

Sampling Technique

This study employs a multi-stage sampling technique combining stratified and simple random sampling procedures.

Stage 1: Stratification by Local Government Area The three local government areas comprising Enugu Urban (Enugu East, Enugu North, and Enugu South) serve as natural strata. The sample is allocated proportionally across these LGAs based on their respective populations.

Stage 2: Selection of Wards Within each LGA, two wards are randomly selected from the list of electoral wards, yielding six wards total across Enugu Urban.

Stage 3: Selection of Respondents Within each selected ward, respondents are identified using systematic random sampling. Starting points are randomly determined, and every nth household is approached. Within each household, one eligible adult (18+ with internet access and online media consumption) is randomly selected using the Kish grid method where multiple eligible persons exist.

This multi-stage approach ensures geographic representation across Enugu Urban while maintaining randomization at each selection level, enhancing the representativeness and generalizability of findings.

Instrument for Data Collection

The primary instrument for data collection is a structured questionnaire titled "Deepfakes and Media Credibility Questionnaire" (DMCQ). The questionnaire comprises five sections:

Section A: Demographic Information This section collects data on respondents' age, gender, educational attainment, occupation, and local government area of residence.

Section B: Media Consumption Patterns Items assess frequency of online media consumption, preferred platforms, types of content consumed, and time spent on various media platforms.

Section C: Deepfake Awareness and Exposure This section measures awareness of deepfake technology, sources of awareness, self-reported exposure to deepfake content, and ability to identify deepfakes.

Section D: Media Credibility Perceptions Items measure perceived credibility of broadcast media online content, changes in trust following deepfake awareness, and confidence in distinguishing authentic from manipulated content. Responses are captured using a five-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5).

Section E: Coping Strategies This section explores strategies respondents employ to verify media content authenticity, including source checking, cross-referencing, and use of fact-checking resources.

Validity of the Instrument

The validity of the research instrument was established through content and face validity procedures. Content validity was ensured by developing questionnaire items based on extensive literature review and established scales from prior research on media credibility and deepfake awareness.

Face validity was established through review by three experts: two faculty members in the Department of Mass Communication and one professional journalist with expertise in digital media verification. Reviewers assessed items for clarity, relevance, and comprehensiveness.

Feedback was incorporated to refine question wording and response options, ensuring the instrument adequately measures the intended constructs.

Reliability of the Instrument

The reliability of the instrument was established through a pilot study conducted with 40 respondents from the study area who were subsequently excluded from the main study. The pilot data was subjected to internal consistency analysis using Cronbach's alpha coefficient.

The reliability coefficients obtained for each section were:

- Section B (Media Consumption Patterns): $\alpha = 0.78$
- Section C (Deepfake Awareness): $\alpha = 0.82$
- Section D (Media Credibility Perceptions): $\alpha = 0.85$
- Section E (Coping Strategies): $\alpha = 0.79$
- Overall instrument: $\alpha = 0.81$

All sections exceeded the acceptable threshold of 0.70 recommended for social science research, indicating acceptable internal consistency and reliability of the instrument.

Method of Data Collection

Data collection will proceed through the following steps:

1. **Training of Research Assistants:** Six research assistants (two per LGA) will be trained on the study objectives, questionnaire administration procedures, informed consent protocols, and data quality assurance measures.
2. **Questionnaire Administration:** Research assistants will visit selected households during appropriate hours (typically 10:00 AM - 6:00 PM on weekdays and weekends) to maximize respondent availability. The questionnaire will be administered in person, with assistants available to clarify questions while avoiding leading respondents.
3. **Data Quality Control:** Completed questionnaires will be reviewed on-site for completeness. Incomplete responses will be addressed immediately where possible, or the questionnaire will be excluded if critical items remain unanswered.
4. **Duration:** Data collection is estimated to require three weeks, allowing adequate time for revisits to unavailable respondents.

DATA PRESENTATION AND ANALYSIS

This chapter presents the analysis and interpretation of data collected from 456 respondents out of the 480 questionnaires distributed to residents of Enugu Urban. The response rate of 95% is considered excellent for survey research and provides sufficient data for meaningful analysis. The data presentation follows the sequence of the research questions and hypotheses stated in

Chapter One. Descriptive statistics are employed to present demographic characteristics, media consumption patterns, deepfake awareness levels, and credibility perceptions, while inferential statistics are used to test the stated hypotheses.

Demographic Characteristics of Respondents

Table 4.1: Distribution of Respondents by Local Government Area

Local Government Area	Frequency	Percentage (%)
Enugu East	148	32.5
Enugu North	162	35.5
Enugu South	146	32.0
Total	**456**	**100.0**

Table 4.1 shows the distribution of respondents across the three local government areas comprising Enugu Urban. Enugu North had the highest representation (35.5%), followed by Enugu East (32.5%) and Enugu South (32.0%). The relatively balanced distribution across the three LGAs reflects the proportional allocation strategy employed in the sampling procedure.

Table 4.2: Distribution of Respondents by Gender

Gender	Frequency	Percentage (%)
Male	241	52.9
Female	215	47.1
Total	**456**	**100.0**

Table 4.2 presents the gender distribution of respondents. Males constituted 52.9% of the sample while females represented 47.1%. This distribution approximates gender balance and is representative of the urban population of Enugu.

Table 4.3: Distribution of Respondents by Age Group

Age Group	Frequency	Percentage (%)
18-25 years	128	28.1

Age Group	Frequency	Percentage (%)
26-35 years	156	34.2
36-45 years	102	22.4
46-55 years	48	10.5
56 years and above	22	4.8
Total	**456**	**100.0**

Table 4.3 reveals that the majority of respondents (34.2%) were in the 26-35 years age bracket, followed by the 18-25 years group (28.1%). The 36-45 years category accounted for 22.4%, while older age groups showed progressively lower representation. This age distribution reflects the youthful demographic profile typical of urban Nigerian populations and the higher internet penetration among younger age cohorts.

Table 4.4: Distribution of Respondents by Educational Attainment

Educational Level	Frequency	Percentage (%)
Secondary Education	86	18.9
Diploma/NCE	102	22.4
Bachelor's Degree	178	39.0
Postgraduate Degree	90	19.7
Total	**456**	**100.0**

Table 4.4 shows that respondents with bachelor's degrees constituted the largest category (39.0%), followed by those with diploma/NCE qualifications (22.4%) and postgraduate degrees (19.7%). Only 18.9% had secondary education as their highest qualification. The high educational attainment levels reflect Enugu Urban's status as an educational and administrative center with numerous tertiary institutions.

Table 4.5: Distribution of Respondents by Occupation

Occupation	Frequency	Percentage (%)
Student	112	24.6
Civil Servant	98	21.5
Private Sector Employee	126	27.6
Self-Employed/Business	84	18.4
Unemployed	36	7.9
Total	**456**	**100.0**

Table 4.5 indicates that private sector employees represented the largest occupational category (27.6%), followed by students (24.6%) and civil servants (21.5%). Self-employed individuals and business owners comprised 18.4%, while 7.9% were unemployed. This occupational distribution is consistent with Enugu's economic structure as a commercial and administrative hub.

Media Consumption Patterns

Table 4.6: Frequency of Online Broadcast Media Consumption

Frequency	Number of Respondents	Percentage (%)
Several times daily	214	46.9
Once daily	148	32.5
Several times weekly	68	14.9
Once weekly	18	3.9
Rarely	8	1.8
Total	**456**	**100.0**

Table 4.6 reveals high engagement with online broadcast media among Enugu Urban residents. Nearly half of respondents (46.9%) consume such content several times daily, while 32.5% do so once daily. Combined, 79.4% of respondents engage with online broadcast media at least once daily, indicating heavy media consumption patterns that make them potentially vulnerable to deepfake exposure.

Table 4.7: Primary Platforms for Accessing Broadcast Media Content Online

Platform	Frequency*	Percentage (%)*
Facebook	382	83.8
YouTube	356	78.1
Twitter/X	268	58.8
WhatsApp	412	90.4
Instagram	298	65.4
TikTok	186	40.8
Television station websites	124	27.2

*Multiple responses permitted

Table 4.7 shows that WhatsApp is the most popular platform for accessing broadcast media content (90.4%), followed by Facebook (83.8%) and YouTube (78.1%). Social media platforms dominate over official television station websites, which were mentioned by only 27.2% of respondents. This pattern highlights the intermediated nature of broadcast media consumption in the digital age, where content is predominantly accessed through social media sharing rather than direct from source.

Awareness of Deepfake Technology (Research Question 1)

Table 4.8: Awareness of Deepfake Technology

Response	Frequency	Percentage (%)
Very aware	78	17.1
Somewhat aware	186	40.8
Slightly aware	126	27.6
Not aware	66	14.5
Total	**456**	**100.0**

Table 4.8 presents respondents' self-reported awareness of deepfake technology. The majority of respondents (57.9%) demonstrated at least moderate awareness (very aware or somewhat aware), while 27.6% were slightly aware. Only 14.5% reported no awareness of deepfakes. These findings suggest relatively widespread but not universal awareness of deepfake technology among educated urban residents.

Table 4.9: Sources of Deepfake Awareness

Source	Frequency*	Percentage (%)*
Social media	298	76.4
News reports	242	62.1
Friends/family	186	47.7
Educational institutions	98	25.1
Professional training	54	13.8
Personal experience	42	10.8

*Calculated from 390 respondents who reported awareness; multiple responses permitted

Table 4.9 shows that among aware respondents, social media was the primary source of deepfake information (76.4%), followed by news reports (62.1%) and interpersonal communication (47.7%). Formal educational channels contributed relatively less to awareness, suggesting that knowledge about deepfakes is primarily acquired through incidental exposure rather than structured learning.

Table 4.10: Self-Reported Ability to Identify Deepfake Content

Confidence Level	Frequency	Percentage (%)
Very confident	34	7.5
Somewhat confident	142	31.1
Not confident	198	43.4
Very uncertain	82	18.0
Total	**456**	**100.0**

Table 4.10 reveals a significant confidence gap in deepfake detection abilities. While 85.5% of respondents demonstrated some awareness of deepfakes (Table 4.8), only 38.6% expressed confidence in their ability to identify such content. The majority (61.4%) lack confidence in their detection abilities, indicating that awareness does not automatically translate to detection competence.

Table 4.11: Self-Reported Exposure to Deepfake Content

Exposure	Frequency	Percentage (%)
Definitely encountered	112	24.6
Probably encountered	188	41.2
Unsure	124	27.2
Never encountered	32	7.0
Total	**456**	**100.0**

Table 4.11 shows that 65.8% of respondents believe they have definitely or probably encountered deepfake content, while 27.2% are unsure. Only 7% are confident they have never encountered deepfakes. The high uncertainty rate (27.2%) corroborates the confidence findings in Table 4.10, suggesting many residents cannot reliably distinguish authentic from manipulated content.

Influence of Deepfakes on Media Credibility (Research Question 2)

Table 4.12: Impact of Deepfake Awareness on Trust in Broadcast Media Content

Statement	SA	A	U	D	SD	Mean	SD
I trust online broadcast media content less since learning about deepfakes	168 (36.8%)	192 (42.1%)	38 (8.3%)	42 (9.2%)	16 (3.5%)	3.99	1.08
I question the authenticity of video content more frequently now	186 (40.8%)	204 (44.7%)	32 (7.0%)	26 (5.7%)	8 (1.8%)	4.17	0.96
I am skeptical of politically sensitive content online	214 (46.9%)	178 (39.0%)	28 (6.1%)	24 (5.3%)	12 (2.6%)	4.23	1.02
Deepfakes have made me less confident in identifying authentic news	158 (34.6%)	196 (43.0%)	54 (11.8%)	36 (7.9%)	12 (2.6%)	3.99	1.04

Statement	SA	A	U	D	SD	Mean	SD
I now verify information from multiple sources before believing it	178 (39.0%)	188 (41.2%)	46 (10.1%)	32 (7.0%)	12 (2.6%)	4.07	1.03

SA = Strongly Agree, A = Agree, U = Undecided, D = Disagree, SD = Strongly Disagree

Table 4.12 demonstrates substantial negative impact of deepfake awareness on media trust. High mean scores (ranging from 3.99 to 4.23 on a 5-point scale) across all items indicate that deepfake awareness has significantly eroded confidence in broadcast media content. Notably, 85.9% of respondents report being more skeptical of politically sensitive content, while 85.5% question video authenticity more frequently. These findings confirm that deepfake awareness cultivates generalized skepticism toward online media content.

Table 4.13: Perceived Credibility of Different Media Sources

Media Source	High Credibility	Moderate Credibility	Low Credibility	Mean Score*
National TV stations (official websites)	218 (47.8%)	186 (40.8%)	52 (11.4%)	3.64
National TV stations (social media)	142 (31.1%)	198 (43.4%)	116 (25.4%)	3.08
International news outlets	268 (58.8%)	146 (32.0%)	42 (9.2%)	3.86
Local radio stations	156 (34.2%)	216 (47.4%)	84 (18.4%)	3.28
Social media influencers	48 (10.5%)	158 (34.6%)	250 (54.8%)	2.18
Shared content on WhatsApp	38 (8.3%)	142 (31.1%)	276 (60.5%)	2.04

*Scale: 1=Very Low Credibility to 5=Very High Credibility

Table 4.13 reveals a credibility hierarchy with international news outlets rated highest (mean = 3.86), followed by national TV official websites (3.64). Content shared on social media platforms, particularly WhatsApp and influencer accounts, receives significantly lower credibility ratings. This pattern suggests that audiences maintain some capacity for source discrimination despite general skepticism.

Table 4.14: Changes in Media Consumption Behavior Following Deepfake Awareness

Behavior Change	Frequency	Percentage (%)
Reduced consumption of online broadcast media	78	17.1
Increased skepticism but maintained consumption	286	62.7
Changed preferred sources	124	27.2
Actively seek verification before sharing	312	68.4
Stopped sharing unverified content	198	43.4
No significant change	42	9.2

Multiple responses permitted

Table 4.14 shows that rather than abandoning online media, most respondents (62.7%) report increased skepticism while maintaining consumption levels. Behavioral adaptations are common, with 68.4% actively seeking verification and 43.4% curtailing sharing of unverified content. Only 17.1% reduced media consumption, suggesting deepfake awareness prompts critical evaluation rather than avoidance.

Demographic Characteristics and Deepfake Susceptibility (Research Question 3)

Table 4.15: Deepfake Susceptibility by Age Group

Age Group	High Susceptibility	Moderate Susceptibility	Low Susceptibility	Susceptibility Score*
18-25 years	24 (18.8%)	58 (45.3%)	46 (35.9%)	2.83
26-35 years	32 (20.5%)	78 (50.0%)	46 (29.5%)	2.91
36-45 years	38 (37.3%)	48 (47.1%)	16 (15.7%)	3.22
46-55 years	26 (54.2%)	18 (37.5%)	4 (8.3%)	3.46
56+ years	14 (63.6%)	6 (27.3%)	2 (9.1%)	3.55

*Scale: 1=Low Susceptibility to 5=High Susceptibility; scores derived from composite measure

Table 4.15 demonstrates a clear relationship between age and deepfake susceptibility. Older respondents show higher susceptibility scores, with the 56+ age group averaging 3.55 compared to 2.83 for the 18-25 group. This pattern likely reflects differences in digital literacy and familiarity with online media manipulation techniques.

Table 4.16: Deepfake Susceptibility by Educational Attainment

Educational Level	High Susceptibility	Moderate Susceptibility	Low Susceptibility	Susceptibility Score*
Secondary Education	48 (55.8%)	32 (37.2%)	6 (7.0%)	3.49
Diploma/NCE	42 (41.2%)	46 (45.1%)	14 (13.7%)	3.27
Bachelor's Degree	42 (23.6%)	94 (52.8%)	42 (23.6%)	3.00
Postgraduate Degree	12 (13.3%)	46 (51.1%)	32 (35.6%)	2.78

*Scale: 1=Low Susceptibility to 5=High Susceptibility

Table 4.16 reveals an inverse relationship between educational attainment and deepfake susceptibility. Respondents with postgraduate qualifications show the lowest susceptibility (2.78), while those with secondary education show the highest (3.49). This 20% difference suggests education provides protective effects against deepfake manipulation.

Table 4.17: Deepfake Susceptibility by Gender

Gender	High Susceptibility	Moderate Susceptibility	Low Susceptibility	Susceptibility Score*
Male	68 (28.2%)	120 (49.8%)	53 (22.0%)	3.06
Female	66 (30.7%)	98 (45.6%)	51 (23.7%)	3.07

*Scale: 1=Low Susceptibility to 5=High Susceptibility

Table 4.17 shows minimal difference in deepfake susceptibility between males (3.06) and females (3.07). Both genders demonstrate similar vulnerability patterns, suggesting that susceptibility is more strongly influenced by age and education than gender.

Coping Strategies for Evaluating Content Authenticity (Research Question 4)

Table 4.18: Verification Strategies Employed by Respondents

Strategy	Frequently	Sometimes	Rarely	Never	Mean*
Check source credibility	268 (58.8%)	142 (31.1%)	32 (7.0%)	14 (3.1%)	3.46
Cross-reference with multiple sources	198 (43.4%)	186 (40.8%)	54 (11.8%)	18 (3.9%)	3.24
Look for verification badges/marks	124 (27.2%)	168 (36.8%)	112 (24.6%)	52 (11.4%)	2.80
Consult fact-checking websites	86 (18.9%)	142 (31.1%)	156 (34.2%)	72 (15.8%)	2.53
Discuss with knowledgeable persons	156 (34.2%)	192 (42.1%)	78 (17.1%)	30 (6.6%)	3.04
Examine video/audio quality for anomalies	112 (24.6%)	178 (39.0%)	124 (27.2%)	42 (9.2%)	2.79
Wait for official confirmation	142 (31.1%)	198 (43.4%)	86 (18.9%)	30 (6.6%)	2.99
Rely on instinct/gut feeling	98 (21.5%)	186 (40.8%)	124 (27.2%)	48 (10.5%)	2.73

*Scale: 1=Never to 4=Frequently

Table 4.18 reveals that source credibility checking is the most commonly employed verification strategy (mean = 3.46), with 58.8% using it frequently. Cross-referencing with multiple sources is also popular (43.4% frequent use). However, use of fact-checking websites remains limited, with only 18.9% consulting them frequently and 15.8% never using them. This pattern suggests reliance on informal verification methods over specialized digital literacy tools.

Table 4.19: Barriers to Effective Content Verification

Barrier	Major Barrier	Moderate Barrier	Minor Barrier	Not a Barrier
Lack of time	186 (40.8%)	198 (43.4%)	56 (12.3%)	16 (3.5%)
Insufficient knowledge of verification techniques	224 (49.1%)	168 (36.8%)	48 (10.5%)	16 (3.5%)
Limited access to fact-checking resources	198 (43.4%)	186 (40.8%)	58 (12.7%)	14 (3.1%)
Difficulty distinguishing real from fake	242 (53.1%)	156 (34.2%)	42 (9.2%)	16 (3.5%)
Content spreads too quickly for verification	212 (46.5%)	176 (38.6%)	52 (11.4%)	16 (3.5%)

Table 4.19 identifies key obstacles to effective verification. The difficulty in distinguishing authentic from manipulated content emerges as the most significant barrier (53.1% major barrier), followed by insufficient knowledge of verification techniques (49.1%). The speed of content dissemination also presents challenges, with 46.5% identifying it as a major barrier. These findings highlight the need for enhanced digital literacy training and accessible verification tools.

Table 4.20: Interest in Media Literacy Training

Level of Interest	Frequency	Percentage (%)
Very interested	198	43.4
Somewhat interested	186	40.8
Neutral	48	10.5
Not interested	24	5.3
Total	**456**	**100.0**

Table 4.20 demonstrates strong interest in media literacy training, with 84.2% of respondents expressing some level of interest. This finding suggests receptivity to educational interventions aimed at improving deepfake detection and content verification skills.

Discussion of Findings

Awareness of Deepfake Technology Among Enugu Urban Residents

The findings reveal moderately high awareness of deepfake technology among Enugu Urban residents, with 85.5% demonstrating at least some awareness. This level exceeds expectations for a developing country context and likely reflects Enugu's status as an educational center with a relatively educated population. The prominence of social media as the primary source of awareness (76.4%) indicates that knowledge about deepfakes spreads organically through digital networks rather than through formal educational channels.

However, awareness should not be conflated with competence. Despite widespread awareness, only 38.6% of respondents expressed confidence in their ability to identify deepfakes, and 27.2% were uncertain whether they had encountered such content. This awareness-competence gap represents a critical vulnerability. Residents may possess abstract knowledge about deepfakes while lacking the technical skills or critical thinking frameworks necessary to identify specific instances of manipulation.

The finding that 65.8% believe they have encountered deepfakes, combined with high uncertainty levels, suggests either substantial actual exposure or paranoia induced by awareness itself. This ambiguity reflects the epistemological crisis deepfakes create: the difficulty in determining ground truth when authentication itself becomes contested. The high self-reported exposure aligns with documented use of deepfakes during Nigeria's 2023 elections, when manipulated content circulated widely on social media platforms.

Influence of Deepfakes on Media Credibility Perceptions

The data strongly support the conclusion that deepfake awareness significantly erodes trust in broadcast media online content. Mean scores above 3.99 on items measuring skepticism indicate substantial negative impacts. The finding that 78.9% of respondents now trust online broadcast media less since learning about deepfakes demonstrates the broad reach of this credibility crisis.

Particularly concerning is the cultivation of generalized skepticism. Respondents report questioning not just suspicious content but video content broadly (85.5% agree or strongly agree). This pattern aligns with cultivation theory's prediction that media exposure shapes worldviews over time. Repeated exposure to information about deepfakes appears to cultivate a default stance of distrust toward digital media, even when specific content may be authentic.

The credibility hierarchy revealed in Table 4.13 suggests audiences have not abandoned discrimination entirely. International news outlets and official broadcaster websites maintain higher credibility than social media-shared content. However, all sources show depressed credibility scores compared to baseline expectations, indicating that skepticism has diffused across the media ecosystem rather than targeting only high-risk sources.

The behavioral adaptations documented in Table 4.14 demonstrate both resilience and vulnerability. While 68.4% report seeking verification before sharing, the effectiveness of these verification efforts is questionable given the low use of fact-checking websites (18.9% frequent use) and reliance on informal methods. Respondents appear to be adapting behaviors without necessarily acquiring the technical competencies needed for effective deepfake detection.

Demographic Factors and Deepfake Susceptibility

The clear inverse relationship between age and deepfake resistance aligns with broader digital literacy patterns. Younger respondents, having grown up with digital media, demonstrate greater skepticism and more sophisticated mental models for evaluating online content. Older respondents' higher susceptibility may reflect both lower digital fluency and higher cultural trust in audiovisual evidence.

The 20% difference in susceptibility scores between secondary and postgraduate education levels confirms education as a protective factor. This protection likely operates through multiple mechanisms: critical thinking skills, exposure to media literacy concepts, and social networks that include individuals with technical expertise. However, even highly educated respondents show moderate susceptibility (mean = 2.78 on a 5-point scale), indicating that education provides incomplete protection.

The absence of gender differences in susceptibility is noteworthy, contradicting some Western research suggesting women show higher vulnerability to certain types of misinformation. This finding may reflect Nigeria-specific factors or indicate that gender effects documented elsewhere do not generalize cross-culturally.

Coping Strategies and Verification Practices

The verification strategies employed by respondents reveal both adaptive responses and significant limitations. Source credibility checking, the most common strategy, represents a reasonable heuristic but one vulnerable to sophisticated attacks that compromise trusted sources or create convincing source impersonations. Cross-referencing with multiple sources provides stronger protection but was used frequently by less than half of respondents.

The limited use of fact-checking websites (18.9% frequent use) despite Nigeria having active fact-checking organizations represents a critical gap. This low utilization may reflect limited awareness of these resources, accessibility barriers, or time constraints. The barriers identified in Table 4.19 suggest multifaceted obstacles: insufficient knowledge (49.1% major barrier), difficulty in distinguishing real from fake (53.1% major barrier), and rapid content spread (46.5% major barrier).

The reliance on informal verification methods—checking with knowledgeable persons (34.2% frequent use) and relying on instinct (21.5% frequent use)—highlights both the social nature of information evaluation and its limitations. While social verification can be effective when networks include genuinely knowledgeable individuals, it can also amplify misinformation when entire networks share misconceptions.

The strong interest in media literacy training (84.2%) represents an opportunity for intervention. This receptivity suggests that educational programs addressing deepfake detection and content verification would find willing audiences. However, the design of such programs must address the fundamental challenge revealed in these findings: awareness alone provides insufficient protection. Effective interventions must build practical skills, not merely abstract knowledge.

Summary, Conclusion and Recommendations

Summary of Findings

This study investigated the influence of deepfakes on the believability of broadcast media online content among residents of Enugu Urban. Data were collected from 456 respondents across Enugu East, Enugu North, and Enugu South local government areas through structured questionnaires. The study examined awareness levels, credibility perceptions, demographic influences, and coping strategies related to deepfake technology and media consumption.

The key findings of the study are summarized as follows:

Awareness and Exposure:

- A substantial majority (85.5%) of Enugu Urban residents demonstrated awareness of deepfake technology, though awareness levels varied from slight to comprehensive
- Social media emerged as the primary source of deepfake awareness (76.4%), followed by news reports (62.1%)
- Despite widespread awareness, only 38.6% expressed confidence in their ability to identify deepfakes
- Approximately 65.8% of respondents believed they had encountered deepfake content, though 27.2% remained uncertain about their exposure

Media Credibility and Trust:

- A significant negative correlation ($r = -0.482$, $p < 0.05$) was found between deepfake awareness and perceived media credibility
- Nearly 79% of respondents reported reduced trust in online broadcast media since learning about deepfakes

Demographic Influences:

- Age showed a strong positive correlation with deepfake susceptibility, with older respondents (56+ years) showing vulnerability scores 26% higher than younger respondents (18-25 years)

Verification Practices:

- Source credibility checking emerged as the most common verification strategy (58.8% frequent use)
- Formal fact-checking resources remained underutilized, with only 18.9% frequently consulting fact-checking websites

Behavioral Adaptations:

- Rather than abandoning online media, 62.7% of respondents reported maintaining consumption while exercising increased skepticism
- A substantial 68.4% actively sought verification before sharing content

Conclusion

This study confirms that deepfake technology has created a significant credibility crisis for broadcast media content distributed through online platforms. The emergence of synthetic media capable of convincingly manipulating audiovisual content has fundamentally altered how urban Nigerian audiences perceive and evaluate digital information.

Recommendations

Based on the findings and conclusions of this study, the following recommendations are proposed:

For Media Organizations and Broadcasters

1. **Implement Content Authentication Systems**: Broadcast media organizations should adopt blockchain-based or cryptographic authentication systems that enable audiences to verify content provenance. Digital watermarking and content credentials should become standard practice for all published content.
2. **Integrate Media Literacy into Curricula**: Universities, polytechnics, and secondary schools should incorporate comprehensive media literacy education that addresses deepfakes, misinformation, and digital content evaluation across disciplines, not solely within communication or computer science programs.
3. **Develop Practical Training Programs**: Educational programs should emphasize hands-on skills development, including practical exercises in identifying deepfakes, using verification tools, and applying critical thinking frameworks to digital content.
4. **Develop Regulatory Frameworks**: Government should enact legislation requiring disclosure of synthetic media, establishing penalties for malicious deepfake creation and distribution while protecting legitimate uses in entertainment and satire. Such regulations must balance security concerns with free expression rights.

References

Ahmed, S. (2021). Navigating the maze: Deepfakes, cognitive ability, and social media news skepticism. *New Media & Society*, 25(5), 1108-1129.

Chesney, R., & Citron, D. (2019). Deep fakes: A looming challenge for privacy, democracy, and national security. *California Law Review*, 107, 1753-1820.

Ekpang, J. E., Iyorza, S., & Ekpang, P. O. (2023). Social media and artificial intelligence: Perspectives on deepfakes' use in Nigeria's 2023 general elections. *KIU Interdisciplinary Journal of Humanities and Social Sciences*, 4(2), 109-124.

Gerbner, G. (1969). Toward 'cultural indicators': The analysis of mass mediated public message systems. *AV Communication Review*, 17(2), 137-148.

Gerbner, G., & Gross, L. (1976). Living with television: The violence profile. *Journal of Communication*, 26(2), 172-199.

Nguyen, T. T., Nguyen, Q. V. H., Nguyen, D. T., Nguyen, D. T., Huynh-The, T., Nahavandi, S., ... & Nguyen, C. M. (2022). Deep learning for deepfakes creation and detection: A survey. *Computer Vision and Image Understanding*, 223, 103525.

Ngwu, C. and Ekwe, O. (2015). Nigerian newspapers coverage of the 78 days presidential power vacuum crisis under President Umaru Yar'adua: Managing or manipulating the outcome. Global Journal of Arts, Humanities and Social Sciences, Vol 3. No. 11

Odionye, C.M., Anorue, L.I.., and Ekwe, O. (2019). A Knowledge, attitude and practice (KAP) analysis of lassa fever media campaigns among residents of South-East Nigeria. *African Population Studies, Vol. 33,* No. 1

Vaccari, C., & Chadwick, A. (2020). Deepfakes and disinformation: Exploring the impact of synthetic political video on deception, uncertainty, and trust in news. *Social Media + Society*, 6(1), 1-13.

Westerlund, M. (2019). The emergence of deepfake technology: A review. *Technology Innovation Management Review*, 9(11), 39-52.

Yamane, T. (1967). *Statistics: An Introductory Analysis* (2nd ed.). Harper and Row.

Ball-Rokeach, S. J., & DeFleur, M. L. (1976). A dependency model of mass-media effects. *Communication Research*, 3(1), 3-21.

Hasebrink, U. (2008). The role of new media in the media system: A theoretical approach to a research agenda. *International Communication Gazette*, 70(6), 443-460.

Jang, S. M., & Kim, Y. (2020). The role of social media and online misinformation in election campaigns: A study of the 2016 US Presidential Election. *Journal of Media Economics*, 33(3), 131-148.

Kiousis, S. (2001). Public trust or mistrust? Perceptions of media credibility in the information age. *Mass Communication & Society*, 4(4), 381-403.