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# SOCIAL MEDIA ALGORITHMS AND YOUTH ENGAGEMENT WITH NAIRA ABUSE CONTENT AMONG STUDENTS OF ALEX EKWUEME FEDERAL UNIVERSITY, NDUFU ALIKE

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**ABSTRACT:** The rise of algorithm-driven social media platforms has intensified the visibility and normalization of Naira abuse content in Nigeria. This study investigates how social media algorithms shape youth engagement with Naira abuse content among 400 undergraduate students of Alex Ekwueme Federal University, Ndufu Alike. Anchored on Algorithmic Media Theory and Social Learning Theory, the study examines how algorithmic recommendation systems amplify sensational currency-related content and how repeated exposure fosters imitation and behavioural normalization among youths. Using a quantitative survey design, the study measured algorithmic exposure, celebrity influence, and youth engagement. Reliability analysis showed strong internal consistency (Cronbach's $\alpha = .89$), while Exploratory Factor Analysis identified three latent constructs: Algorithmic Exposure, Celebrity Influence, and Youth Engagement. All items met the retention criteria (factor loadings $\geq .50$) and were included in the final analysis; only the highest-loading items are displayed in the results table for brevity. Correlation analysis revealed a strong positive association between algorithmic exposure and youth engagement ($r = .62$, $p < .001$). Hierarchical regression further showed that algorithmic exposure significantly predicted youth engagement ($\beta = .54$, $p < .001$), even after controlling for demographics and celebrity influence. Findings demonstrate that algorithms not only amplify visually stimulating Naira abuse content but also reinforce behavioural modelling processes described in Social Learning Theory, whereby youths imitate repeated, high-status behaviours displayed by celebrities. The study concludes that algorithmic amplification and observational learning jointly normalize harmful currency-related practices. It recommends enhanced algorithmic transparency, stronger regulatory collaboration, and youth-focused digital literacy interventions to mitigate the spread and influence of Naira abuse content.

**Keywords:** Social Media Algorithms, Naira Abuse, Youth Engagement, Algorithmic Amplification, Celebrity Influence

## INTRODUCTION

The rapid expansion of social media has reshaped how individuals engage with information, culture, and national symbols. Platforms such as TikTok, Instagram, and Snapchat now play a central role in youth identity formation, particularly in the Global South, where mobile-first internet adoption is accelerating (Poushter et al., 2023). These platforms operate through algorithmic recommendation systems that curate content based on predicted engagement, thereby shaping visibility, influencing behaviour, and normalizing even harmful or illegal practices (Bucher, 2018; Gillespie, 2020).

In Nigeria, this dynamic is evident in the increasing visibility of Naira abuse, such as spraying, trampling, mutilation, and ostentatious display of the national currency despite its prohibition under the Central Bank of Nigeria Act (2007). Celebrity posts depicting such acts attract high engagement and are algorithmically amplified, raising concerns about how platform infrastructures contribute to the normalization of culturally sensitive or unlawful behaviours (Cotter, 2019). Global research similarly shows that algorithms encourage sensational, emotionally charged, or controversial content (Cinelli et al., 2021; Ribeiro et al., 2020), and that influencers often escalate provocative performances to sustain visibility (Kaye et al., 2022; Abidin, 2021).

However, African scholarship has paid limited attention to the intersection of algorithmic systems, celebrity culture, and youth digital participation. Studies in Nigeria examine celebrity influence (Ojebuyi & Salawu, 2022) and the socio-cultural dimensions of Naira abuse (Adebayo, 2018), but rarely the technological infrastructures that amplify such content. This gap is significant given Nigeria's predominantly youthful population and high social media consumption (Statista, 2024), which intensifies exposure to algorithmically curated norms.

The persistence of Naira's abuses online despite repeated warnings and arrests of high-profile figures such as Bobrisky and Cubana Chief Priest suggests that enforcement alone is insufficient without addressing the algorithmic mechanisms that drive visibility. Youth engagement is also active rather than passive; repeated exposure to algorithms increases imitation and behavioural normalization (Bandura, 2001; Fardouly et al., 2020). In a context marked by economic hardship and aspirational celebrity culture, algorithmic amplification may further glamorize illegal or unethical practices.

This study, therefore, investigates how social media algorithms shape youth engagement with Naira abuse content, drawing on 400 active undergraduate students at Alex Ekwueme Federal University, Ndufu Alike Ikwo, and using Algorithmic Media Theory to examine the interplay between digital infrastructures, cultural practices, and behavioural outcomes. The research contributes to global debates on algorithmic amplification, advances African digital media scholarship, and informs policy discussions on currency protection, youth digital literacy, and social media regulation. The study also draws on Social Learning Theory, which explains how repeated exposure to high-status models, such as celebrities, shapes imitation, behavioural adoption, and the normalization of Naira abuse practices among youths.

## The Problem

Despite legal prohibitions and recent arrests of high-profile offenders, Naira abuse continues to proliferate on social media, where platforms such as TikTok, Instagram, and Snapchat algorithmically amplify visually sensational currency-related content. While global research shows that algorithms can intensify exposure to harmful behaviours, empirical evidence from African contexts remains scanty. Nigerian scholarship has focused largely on cultural and ethical dimensions of Naira misuse, with limited attention to the technological infrastructures that heighten its visibility or the behavioural consequences of repeated algorithmic exposure among youths.

Given Nigeria's large youth population, high social media usage, economic peculiarity, and aspirational celebrity culture, algorithmic amplification may normalise Naira abuse, glamorise materialistic lifestyles, and weaken respect for national symbols. However, the extent to which algorithmic exposure predicts youth engagement remains unclear. This underscores the need for systematic investigation into how algorithms shape the visibility, normalisation, and imitation of Naira abuse, and whether algorithmic influence surpasses celebrity behaviour in driving youth engagement at Alex Ekwueme Federal University, Ndufu Alike Ikwo.

**Research Questions**

1. What is the exposure of students of AE- FUNAI to Naira abuse content on social media?
2. What types of Naira abuse content are algorithmically amplified on social media platforms used by AE FUNAI Students
3. How does algorithmic exposure influence AE-FUNAI students' engagement with Naira abuse content on platforms such as TikTok, Instagram, and Snapchat?
4. What is the relative influence of algorithmic exposure and celebrity behaviour on AE-FUNAI students' engagement with Naira abuse content?

## LITERATURE REVIEW

### Conceptual Clarification: Algorithm

An algorithm refers to a structured, step-by-step computational procedure used by digital platforms to process data, make predictions, and determine what content becomes visible to users. Gillespie (2014) describes algorithms as "encoded procedures for transforming input data into desired outputs," highlighting their role as invisible yet powerful mediators of online experience. On social media platforms, algorithms analyse user behaviour such as likes, watch time, comments, and search patterns—to predict what content will maximise engagement. This predictive logic shapes what appears on feeds such as TikTok's *For You Page* or Instagram's *Explore* tab, meaning that visibility is not neutral but the outcome of continuous algorithmic sorting and ranking.

In the context of this study, algorithmic recommendation systems are understood as computational mechanisms that amplify visually stimulating, emotionally charged, or sensational content, including Naira abuse videos, because such content aligns with platform optimisation goals. As the study argues, platforms operate through algorithmic recommendation systems that curate content based on predicted engagement. This conceptualisation is central to Algorithmic Media Theory, which positions algorithms as cultural gatekeepers that shape user behaviour, attention, and social norms.

**Social Media Algorithms and Content Amplification**

Social media algorithms now play a central role in curating, ranking, and distributing information across digital platforms. These systems prioritize content based on predicted engagement and platform-specific optimization goals, thereby shaping what users see and how they interact with it (Gillespie, 2020). Recommendation features such as TikTok's for You Page and Instagram's Explore feed are designed to maximise attention by amplifying emotionally charged, visually stimulating, or socially provocative content (Bucher, 2018; Kaye et al., 2022). As a result, sensational, controversial, and risky material often receives disproportionate visibility (Cinelli et al., 2021).

Empirical studies show that algorithmic curation can inadvertently promote harmful behaviours. Ribeiro et al. (2020) found that YouTube's recommendation system steered users towards increasingly extreme content, while Papadamou et al. (2022) demonstrated that TikTok rapidly exposes users to dangerous challenges within minutes of account creation. These findings underscore the structural power of algorithms in shaping cultural visibility and behavioural norms. In Nigeria, although research on algorithmic amplification is limited, scholars note that platforms disproportionately promote celebrity content, political sensationalism, and conspicuous displays of wealth (Ojebuyi & Salawu, 2022). This environment is conducive to the amplification of Naira abuse content, which has both visually striking and emotionally charged qualities that algorithms tend to reward.

**Youth Digital Behaviour and Algorithmic Influence**

Youth populations are particularly vulnerable to algorithmic influence due to high levels of digital immersion, identity exploration, and peer-driven engagement (Fardouly et al., 2020). Social media functions as a key site for social comparison, aspiration, and behavioural modelling (Vaterlaus et al., 2021). Algorithms intensify these processes by repeatedly exposing users to content aligned with their interests or emotional triggers, creating what Pariser (2011) terms "filter bubbles."

Repeated algorithmic exposure has been shown to normalise harmful behaviours. O'Reilly et al. (2018) found that adolescents' exposure to self-harm content on social media contributed to emotional distress and behavioural contagion, highlighting how repeated visibility of harmful material, regardless of platform intent, can shape youth perceptions and actions. Although the study did not focus specifically on algorithmic mechanisms, its findings underscore the broader risks associated with persistent exposure to harmful content in digital environments. While Kircaburun et al. (2020) reported that algorithmically amplified gambling content increased youth participation in online betting. In Nigeria, where youth unemployment and economic peculiarity heighten the appeal of aspirational lifestyles, algorithmic exposure to celebrity wealth displays may reinforce materialistic values and risky behaviours (Olanrewaju, 2021). Consequently, Naira abuse content often framed as entertainment or celebration may be internalised as socially acceptable or desirable.

**Celebrity Influence, Digital Culture, and Symbolic Power**

Celebrities function as influential cultural intermediaries whose behaviours shape public norms, especially among youth (Abidin, 2021). Digital celebrity culture is characterized by curated self-presentation, conspicuous consumption, and the strategic use of spectacle to maintain visibility (Marwick, 2015). These dynamics are amplified in African contexts, where celebrity lifestyles often symbolise success, mobility, and escape from socio-economic constraints (Ndlovu, 2020).

Research shows that celebrity displays of wealth on social media significantly influence youth aspirations and behaviours. For instance, Djafarova and Trofimenko (2019) found that celebrity influencers shape young people's perceptions of luxury, success, and social status. In Nigeria, celebrities such as musicians, actors, and socialites frequently showcase extravagant lifestyles, which youths interpret as markers of achievement (Ojebuyi & Salawu, 2022).

Recent Nigerian scholarship reinforces this pattern. Nwankiti et al. (2024) found that university students perceive celebrity-driven Naira abuse, particularly by figures such as Bobrisky and Cubana Chief Priest, as highly influential in shaping youth attitudes toward wealth, legality, and social values. Their study revealed that celebrity displays of Naira abuse on social media contribute to the glamorization of the get-rich-quick culture and weaken respect for national symbols. This aligns with Social Learning Theory, which posits that youths imitate behaviours modelled by high-status individuals. By integrating celebrity spectacle with algorithmic amplification, Nigerian youths are exposed to repeated cues that normalise currency misuse and elevate it as a symbol of success.

Naira abuse content fits within this broader culture of conspicuous consumption. Videos of celebrities spraying money at events, flaunting cash bundles, or engaging in ostentatious displays serve as symbolic performances of power and prestige. When amplified by algorithms, these performances gain cultural legitimacy and become aspirational templates for youth.

## Theoretical Framework

### Algorithmic Media Theory (AMT)

Algorithmic Media Theory was advanced by scholars such as Tarleton Gillespie (2014, 2020) and Taina Bucher (2018), who argue that digital platforms rely on opaque computational systems to curate, rank, and distribute content. The theory posits that algorithms function as gatekeepers that shape what users see, how they interact with content, and what becomes culturally visible online.

Scholars working within Algorithmic Media Theory argue that algorithms shape cultural visibility not as neutral technical tools but as socio-technical systems embedded with platform priorities such as engagement maximisation, virality, and monetisation. Rather than simply reflecting user preferences, algorithms actively structure what becomes visible by ranking and amplifying content that aligns with platform optimisation goals. This means that visibility is engineered: emotionally charged, visually striking, or provocative material is more likely to be promoted because it generates higher interaction. Over time, users become conditioned by these patterns of exposure, developing preferences, expectations, and behaviours that mirror the algorithmic logic of the platforms they use.

Gillespie (2020) notes that algorithms “actively participate in the production of culture,” while Bucher (2018) argues that users develop “algorithmic imaginaries” beliefs about how platforms decide what to show them. Scholars such as Cinelli et al. (2021) and Papadamou et al. (2022) have shown that algorithms often amplify harmful or risky content because such material generates high engagement.

In the Nigerian context, Ojebuyi and Salawu (2022) observe that platforms disproportionately promote celebrity content and conspicuous displays of wealth, creating fertile ground for the amplification of Naira abuse content.

**Major Tenets of Social Learning Theory (SLT)**

Social Learning Theory was developed by Albert Bandura (1977, 2001). The theory argues that individuals learn behaviours through observation, imitation, and modelling, especially when those behaviours are displayed by high-status or influential figures.

Major Tenets of SLT are observational learning. People imitate behaviours they repeatedly see. Also, Behaviours displayed by celebrities, influencers, or authority figures are more likely to be copied because behaviours that appear rewarded (likes, fame, praise) are more likely to be adopted. Finally, Media content, especially videos, serves as a powerful source of behavioural cues.

Social Learning Theory emphasises that individuals acquire behaviours through observation, imitation, and modelling, particularly when the behaviour is displayed by high-status or socially influential figures. In digital environments, repeated exposure to such behaviours increases the likelihood of imitation, especially when they appear to be rewarded with likes, comments, or public admiration. Media content, especially short-form videos, serves as a powerful source of symbolic cues that shape behavioural expectations. For youths navigating identity formation and peer comparison, these cues become especially salient, making them more likely to internalise and reproduce behaviours they repeatedly encounter online.

Bandura (2001) emphasizes that digital media environments intensify modelling because they provide continuous exposure to symbolic behaviours. Fardouly et al. (2020) and Vaterlaus et al. (2021) show that youths are particularly susceptible to imitating online behaviours due to identity exploration and peer influence. In Nigeria, Nwankiti et al. (2024) found that celebrity-driven Naira abuse significantly shapes youth perceptions of wealth, legality, and social status.

**Combined Relevance of AMT and SLT**

Together, Algorithmic Media Theory and Social Learning Theory provide a complementary explanatory framework for this study. While AMT clarifies how platform infrastructures determine the visibility and circulation of Naira abuse content, SLT explains how youths internalise and imitate such behaviours once they become repeatedly exposed to them. The combination of the two theories therefore captures the structural and behavioural dimensions of the phenomenon: algorithms amplify the content, and observational learning drives its adoption and normalisation.

**Empirical Review: Algorithmic Governance, Platform Responsibility, and Regulatory Gaps**

Nigerian scholarship has examined the socio-cultural dimensions of Naira abuse, with Adebayo (2018) emphasizing its ethical implications and Ogunleye (2017) highlighting its cultural embeddedness in celebratory practices. More recent work by Nwankiti et al. (2024) shows that youths perceive celebrity-driven Naira abuse as both a cultural performance and a social problem, noting its contribution to moral decline, reinforcement of materialistic values, and shifts in perceptions of legality and national identity. These studies underscore the need to understand Naira abuse not only as a cultural practice but as a digitally mediated behaviour shaped by celebrity visibility and platform dynamics.

Globally, concerns about algorithmic governance highlight the power of platforms to shape user behaviour through opaque computational systems (Beer, 2017). Scholars argue that limited transparency around algorithmic operations hinders regulatory oversight and allows harmful content to proliferate (Pasquale, 2015). Research further shows that platforms often act slowly in moderating harmful content unless pressured by governments or civil society (Gorwa, 2019), and enforcement remains inconsistent, particularly in the Global South, where regulatory capacity is weaker (Mare, 2020). In Nigeria, agencies such as the National Broadcasting Commission (NBC) and the Nigerian Communications Commission (NCC) have limited jurisdiction over global platforms, creating significant enforcement gaps. This regulatory vacuum enables harmful content, including Naira abuse, to circulate widely without meaningful accountability.

Despite extensive global scholarship on algorithmic amplification and youth digital behaviour, significant gaps remain, including limited African-based empirical research, scarce studies linking algorithmic exposure to culturally sensitive illegal behaviours such as Naira abuse, and insufficient integration of algorithmic theory with youth behavioural studies in the Global South. This study addresses these gaps by providing quantitative evidence on how algorithmic exposure shapes youth engagement with Naira abuse content in Nigeria.

## METHOD OF THE STUDY

This study employed a quantitative cross-sectional survey design to investigate how social media algorithms influence youth engagement with Naira abuse content. The design enabled the collection of standardized data suitable for statistical analysis of relationships among algorithmic exposure, celebrity influence, and youth engagement.

### Population and Sample Size

The population consisted of all undergraduate students of Alex Ekwueme Federal University, Ndufu-Alike (AE-FUNAI), estimated at over 12,000. Using Cochran's formula at a 95% confidence level and 5% margin of error, a minimum sample of 384 was obtained. This was increased to 400 to enhance representativeness and account for non-responses.

**Sampling Technique**

Purposive sampling was used to select students who actively use algorithm-driven platforms such as TikTok, Instagram, and Snapchat and who had prior exposure to Naira abuse content. This ensured that respondents were relevant to the study's objectives.

**Instrument for Data Collection**

Data were collected using a structured questionnaire comprising four sections: demographics, algorithmic exposure (8 items), celebrity influence (7 items), and youth engagement (9 items). All items were measured on a 5-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). The questionnaire items were adapted from validated digital media behaviour scales and tailored to the Nigerian context.

**Data Collection Procedure**

The questionnaire was administered both physically and electronically over four weeks. Research assistants distributed the instrument across faculties, hostels, and student centres. Of the 430 questionnaires distributed, 400 were completed correctly and returned, giving a response rate of 93%. These 400 responses formed the dataset used for all statistical analyses.

**Validity and Reliability**

Content validity was ensured through expert review, while a pilot test with 50 students confirmed clarity and suitability. Reliability analysis produced strong internal consistency across all scales ($\alpha$ = .86–.90). Exploratory Factor Analysis confirmed a three-factor structure consistent with the constructs measured. All items met the retention criteria (loading $\geq$ .50, cross-loading $\leq$ .30) and were retained for subsequent analyses. Only the four highest-loading items per construct are displayed in Table 3 for clarity; the full factor-loading matrix is available in Appendix X.

**Method of Data Analysis**

Data were analysed using the Statistical Package for the Social Sciences (SPSS). The analysis followed a multistage procedure involving descriptive statistics, reliability testing, Exploratory Factor Analysis (EFA), correlation analysis, and hierarchical multiple regression. Descriptive statistics summarized demographic characteristics and mean scores of key constructs. EFA was used to confirm the underlying factor structure of the measurement scales. Pearson correlation assessed the strength and direction of relationships among variables, while hierarchical regression determined the predictive influence of algorithmic exposure and celebrity influence on youth engagement, controlling for demographic factors. All statistical assumptions were checked and met before conducting the analyses.

## RESULTS

### Descriptive Statistics

A total of 400 valid responses were analysed. Table 1 presents the demographic characteristics of respondents.

**Table 1: Demographic Characteristics of Respondents (N = 400)**

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| **Age** | 18-24 | 162 | 40.5% |
| | 25-30 | 148 | 37.0% |
| | 31-35 | 90 | 22.5% |
| **Gender** | Male | 208 | 52.0% |
| | Female | 192 | 48.0% |
| **Daily Social Media Use** | < 2 hours | 46 | 11.5% |
| | 2-4 hours | 118 | 29.5% |
| | 4-6 hours | 156 | 39.0% |
| | > 6 hours | 80 | 20.0% |

*Source: Field survey 2025*

Respondents reported experiencing a high level of algorithmically recommended content, with average scores indicating substantial exposure and engagement. Specifically, the mean score for Algorithmic Exposure was 3.87 with a standard deviation of 0.71. For Celebrity Influence, the mean was 3.62 with a standard deviation of 0.76. Youth Engagement had a mean score of 3.94 and a standard deviation of 0.68. Overall, these values suggest that participants are generally highly exposed to and engaged with such content.

### Reliability Analysis

Cronbach's alpha values demonstrated strong internal consistency across all scales.

**Table 2: Reliability Coefficients for Study Scales**

| Scale | Number of items | Cronbach's α |
|---|---|---|
| **Algorithmic Exposure** | 8 | 0.88 |
| **Celebrity Influence** | 7 | 0.86 |
| **Youth Engagement** | 9 | 0.90 |
| **Overall Reliability** | - | 0.89 |

*Source: Field survey 2025*

All α values exceeded the recommended threshold of 0.70, confirming reliability.

**Exploratory Factor Analysis (EFA)**

**Sampling Adequacy**

The Kaiser-Meyer-Olkin measure of sampling adequacy is 0.91, indicating excellent suitability for factor analysis. Bartlett's Test of Sphericity yielded a chi-square value of 4128.54 with 276 degrees of freedom and was statistically significant ($p < .001$), confirming that the data are appropriate for factor analysis.

**Factor Extraction**

Principal Component Analysis with Varimax rotation extracted three factors with eigenvalues > 1, explaining 67.4% of total variance.

**Table 3: Principal Component Analysis with Varimax rotation**

| Item | Algorithmic Exposure | Celebrity Influence | Youth Engagement |
|---|---|---|---|
| **AE1** | .78 | - | - |
| **AE2** | .74 | - | - |
| **AE3** | .71 | - | - |
| **AE4** | .69 | - | - |
| **CI1** | - | .82 | - |
| **CI2** | - | .77 | - |
| **CI3** | - | .73 | - |
| **CI4** | - | .70 | - |
| **YE1** | - | - | .81 |
| **YE2** | - | - | .78 |
| **YE3** | - | - | .74 |
| **YE4** | - | - | .72 |

*Source: Field Survey 2025*

All retained items loaded ≥ .70 on their respective factors, confirming a clean factor structure. Although the instrument contained 8 Algorithmic Exposure items, 7 Celebrity Influence items, and 9 Youth Engagement items, all items that met the loading threshold were retained. Table 3 presents only the strongest-loading items for ease of interpretation.

**Correlation Analysis**

Pearson correlations were computed among the three composite variables.

**Table 4: Correlation Matrix**

| Variable | 1 | 2 | 3 |
|---|---|---|---|
| 1. Algorithmic Exposure | - | .48** | .62** |
| 2. Celebrity Influence | .48** | - | .55** |
| 3. Youth Engagement | .62** | .55** | - |

*Note: p < .01*

Algorithmic Exposure shows a strong positive correlation with Youth Engagement (r = .62). Celebrity Influence also correlates strongly with Youth Engagement (r = .55). The two predictors are moderately correlated (r = .48), but not enough to indicate multicollinearity.

**Multiple Regression Analysis**

A hierarchical regression was conducted to determine the predictive influence of Algorithmic Exposure and Celebrity Influence on Youth Engagement.

**Model Summary**

**Table 5: Hierarchical Regression Model Summary**

| Model | Predictors | R | $R^2$ | Adjusted $R^2$ | $\Delta R^2$ | F |
|---|---|---|---|---|---|---|
| **Model 1** | Demographics (Age, Gender, Social Media Use) | .29 | .08 | .06 | – | 11.49 |
| **Model 2** | + Algorithmic Exposure, Celebrity Influence | .71 | .50 | .49 | .42 | 78.80 |

*Source: Field survey 2025*

Adding Algorithmic Exposure and Celebrity Influence significantly improved model fit, as reflected in the increase in F-statistics from Model 1 to Model 2

**Regression Coefficients**

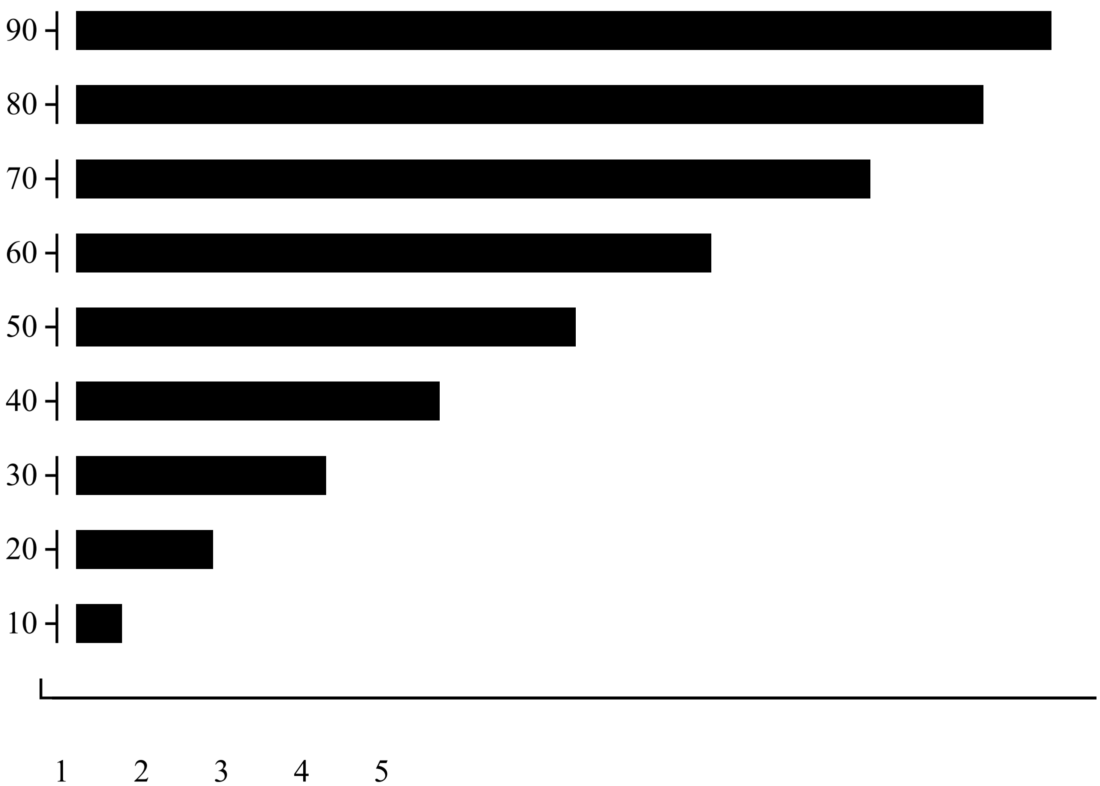
**Table 6: Regression Coefficients for Predicting Youth Engagement**

| Predictor | β | SE | T | P |
|---|---|---|---|---|
| **Age** | -.04 | .03 | -1.21 | .227 |
| **Gender** | .06 | .04 | 1.48 | .140 |
| **Social media use** | .18 | .03 | 4.92 | < .001 |
| **Algorithmic exposure** | .54 | .04 | 12.87 | < .001 |
| **Celebrity Influence** | .31 | .04 | 7.44 | < .001 |

As shown in Table 6, Algorithmic Exposure is the most significant predictor of youth engagement, with a beta coefficient of .54. Celebrity influence also plays a notable role in predicting engagement, with a beta of .31. In contrast, demographics have little predictive power, except in the case of social media use frequency.

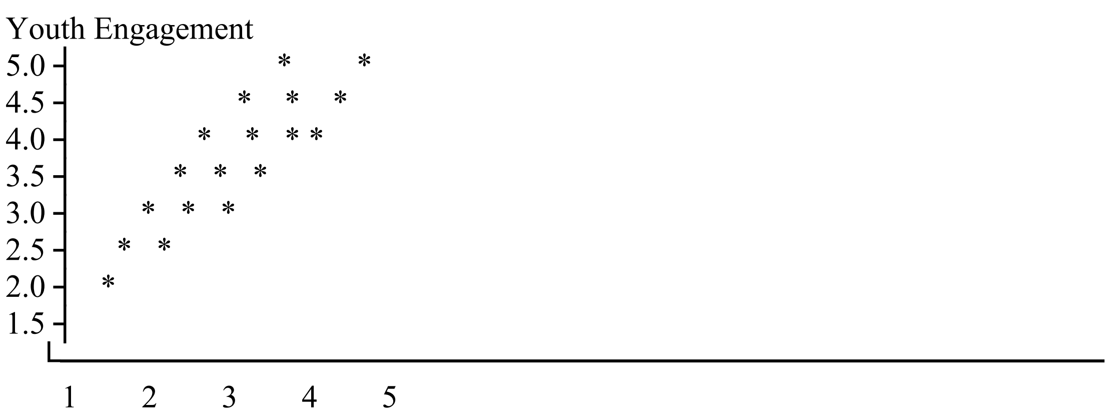
**Data Visualization**

**Figure 1: Frequency**




Algorithmic Exposure Score. Most respondents scored between 3 and 5, indicating moderate-to-high algorithmic exposure.

**Figure 2: Scatterplot of Algorithmic Exposure vs. Youth Engagement****



Algorithmic Exposure: The upward trend reflects the strong positive correlation ($r = .62$, $p < .001$).

**Summary of Key Findings**

The study revealed that youths in AE-FUNAI experience high levels of algorithmically driven exposure to Naira abuse content, indicating that such material is actively promoted by platform recommendation systems rather than encountered by chance. Reliability analysis confirmed strong internal consistency across all measurement scales ($\alpha = .86–.90$), and Exploratory Factor Analysis validated a three-factor structure: Algorithmic Exposure, Celebrity Influence, and Youth Engagement, explaining 67.4% of total variance.

Correlation results showed a strong positive relationship between algorithmic exposure and youth engagement ($r = .62$), while hierarchical regression identified algorithmic exposure as the dominant predictor of engagement ($\beta = .54$), surpassing celebrity influence ($\beta = .31$). The final model accounted for 50% of the variance in youth engagement, demonstrating that algorithmic amplification and celebrity behaviour jointly shape how Nigerian youths interact with Naira abuse content, with algorithms exerting the stronger influence.

**DISCUSSION**

The purpose of this study was to examine how social media algorithms influence youth engagement with Naira abuse content. The findings provide compelling evidence that algorithmic recommendation systems play a central role in shaping youth exposure to and interaction with harmful currency-related content.

The stronger predictive power of algorithmic exposure ($\beta = .54$) compared to celebrity influence ($\beta = .31$) suggests that platform infrastructures exert a more consistent and pervasive influence on youth behaviour than individual celebrity actions. While celebrities provide symbolic models that youths may imitate, algorithms determine the frequency, visibility, and repetition of such content. This aligns with Algorithmic Media Theory, which emphasises that platform logics, not individual actors, shape cultural visibility and behavioural cues. In contrast, Social Learning Theory explains why celebrity behaviour still matters, but the lower beta coefficient indicates that modelling alone is insufficient without algorithmic reinforcement. In the Nigerian context, where youths spend long hours on TikTok, Instagram, and Snapchat, algorithmic repetition may normalise Naira abuse more powerfully than celebrity status itself, making the platform, not the celebrity, the primary driver of behavioural adoption.

The high mean scores for algorithmic exposure and youth engagement indicate that Naira abuse content is not encountered randomly but is actively promoted by platform algorithms. This aligns with Algorithmic Media Theory, which argues that algorithms prioritize visually stimulating and emotionally charged content to maximize engagement. The strong correlation ($r = .62$) and dominant regression coefficient ($\beta = .54$) for algorithmic exposure confirm that algorithmic amplification significantly drives youth engagement.

The findings also support Social Learning Theory, which posits that individuals imitate behaviours modelled by influential figures. Celebrity influence significantly predicted youth engagement ($\beta = .31$), demonstrating that celebrity displays of Naira abuse serve as behavioural cues that youths internalize and reproduce. When combined with algorithmic amplification, these cues become even more powerful, creating a feedback loop that normalizes Naira abuse as entertainment or a symbol of success.

The regression model explaining 50% of the variance in youth engagement underscores the structural power of digital platforms in shaping cultural practices. The results suggest that enforcement alone cannot curb Naira abuse without addressing the algorithmic systems that amplify such content. Overall, the findings highlight the need for a multi-layered approach involving platform accountability, regulatory oversight, and youth digital literacy.

**Conclusion**

This study concludes that social media algorithms are not passive intermediaries but active cultural actors that shape youth behaviour by amplifying Naira abuse content. Algorithmic exposure emerged as the strongest predictor of youth engagement, surpassing even celebrity influence. The findings demonstrate that repeated algorithmic exposure and observational learning jointly normalize harmful currency-related practices among Nigerian youths.

The study contributes to African digital media scholarship by providing empirical evidence on algorithmic amplification in a Global South context and highlights the urgent need for regulatory and educational interventions.

However, the contribution of this study should be interpreted in light of certain limitations. The use of a single university sample limits the generalisability of the findings to the wider Nigerian youth population, particularly given regional, socioeconomic, and institutional differences in digital media use. In addition, the cross-sectional design captures associations at a single point in time and cannot establish causal relationships among algorithmic exposure, celebrity influence, and youth engagement. Future studies employing multi-site sampling or longitudinal designs would provide a more robust understanding of how these dynamics evolve across different youth populations and over time.

**Recommendations**

The study recommends strengthening algorithmic transparency by requiring social media platforms to disclose how their recommendation systems amplify content and to collaborate with Nigerian regulators to enforce currency-misuse laws. It also calls for updated regulatory frameworks that explicitly address the digital dissemination of Naira abuse, alongside youth-focused digital literacy programs that teach algorithm awareness and critical evaluation of online content.

Additionally, partnerships with celebrities are encouraged to promote positive messaging, while platforms should enhance moderation through automated detection, warning labels, and reduced algorithmic promotion of harmful currency-related content. Finally, the study highlights the need for further research on algorithmic influence in African contexts to better understand how digital infrastructures shape cultural norms and legal compliance.

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**APPENDIX I**

**QUESTIONNAIRE**

**Title:** *Social Media Algorithms and Youth Engagement with Naira Abuse Content among Undergraduate Students of AE-FUNAI*

**Instruction:** Please tick (✓) the option that best represents your opinion. All responses will be treated with strict confidentiality and used solely for academic purposes.

**Response Key:** 1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

**SECTION A: DEMOGRAPHIC INFORMATION**

1. **Age:** ☐ 18–24 ☐ 25–30 ☐ 31–35
2. **Gender:** ☐ Male ☐ Female
3. **Faculty:** ☐ Humanities ☐ Social Sciences ☐ Management Sciences ☐ Sciences ☐ Education ☐ Other (specify): ___________
4. **Daily Social Media Use:** ☐ Less than 2 hours ☐ 2–4 hours ☐ 4–6 hours ☐ More than 6 hours
5. **Platforms You Use Frequently (tick all that apply):** ☐ TikTok ☐ Instagram ☐ Snapchat ☐ Facebook ☐ Twitter/X ☐ YouTube

### SECTION B: ALGORITHMIC EXPOSURE (AE)

*Please indicate how often social media algorithms expose you to Naira abuse content.*

| No. | Item | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| AE1 | TikTok/Instagram/Snapchat frequently recommend videos showing Naira abuse. | ☐ | ☐ | ☐ | ☐ | ☐ |
| AE2 | I often see Naira abuse content on my "For You Page" or "Explore" feed. | ☐ | ☐ | ☐ | ☐ | ☐ |
| AE3 | The more I watch entertainment content, the more Naira abuse videos appear. | ☐ | ☐ | ☐ | ☐ | ☐ |
| AE4 | I see Naira abuse videos even when I am not searching for them. | ☐ | ☐ | ☐ | ☐ | ☐ |
| AE5 | Social media algorithms push celebrity money-spraying videos to my feed. | ☐ | ☐ | ☐ | ☐ | ☐ |
| AE6 | Naira abuse videos trend easily on my social media platforms. | ☐ | ☐ | ☐ | ☐ | ☐ |
| AE7 | I often receive repeated suggestions of currency related content. | ☐ | ☐ | ☐ | ☐ | ☐ |
| AE8 | My feed shows more Naira abuse content when I engage with similar videos. | ☐ | ☐ | ☐ | ☐ | ☐ |

### SECTION C: CELEBRITY INFLUENCE (CI)

*Please indicate how celebrity behaviour affects your perception of Naira abuse.*

| No. | Item | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| CI1 | I pay attention to how celebrities display money online. | ☐ | ☐ | ☐ | ☐ | ☐ |
| CI2 | Celebrities make Naira abuse look glamorous or entertaining. | ☐ | ☐ | ☐ | ☐ | ☐ |
| CI3 | I follow celebrities who frequently post money-spraying videos. | ☐ | ☐ | ☐ | ☐ | ☐ |
| CI4 | Celebrity behaviour influences how youths view Naira abuse. | ☐ | ☐ | ☐ | ☐ | ☐ |
| CI5 | Celebrities shape trends involving money displays. | ☐ | ☐ | ☐ | ☐ | ☐ |
| CI6 | I often watch events where celebrities spray money. | ☐ | ☐ | ☐ | ☐ | ☐ |
| CI7 | Celebrity posts make Naira abuse appear socially acceptable. | ☐ | ☐ | ☐ | ☐ | ☐ |

**SECTION D: YOUTH ENGAGEMENT (YE)**

*Please indicate how you engage with Naira abuse content online.*

| No. | Item | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| YE1 | I like or react to Naira abuse videos when I see them. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE2 | I comment on or share Naira abuse content. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE3 | I watch Naira abuse videos to the end. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE4 | I follow pages that post money-spraying content. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE5 | I save or revisit Naira abuse videos. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE6 | I imitate poses or behaviours seen in Naira abuse videos. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE7 | I enjoy watching celebrities spray money at events. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE8 | I participate in online discussions about Naira abuse. | ☐ | ☐ | ☐ | ☐ | ☐ |
| YE9 | I have posted or reposted Naira abuse content before. | ☐ | ☐ | ☐ | ☐ | ☐ |