Impact of Media Content on the Moral Construct of Youth: A Study at Tamale Technical University

ABSTRACT

Aims: The availability of the mass media and the potential broad use of them are two of the key factors that can shape and distort the morality and behavioral nature of people within a territorial space depending on their exposure to its positive or negative aspects. This article identified the influence of social media on the behavior of students, the role of media content in promoting social vices, and the programs most cherished by the youth in the media.

Study design: The study employed a cross-sectional design.

Place and Duration of Study: Tamale Technical University, between November 2023 and December 2024.

Methodology: We chose a sample size of 240 students using the stratified sampling technique. Data was obtained solely from primary sources using a structured questionnaire as the data collection instrument. We analyzed the data using a combination of frequency counts and simple percentages. We employed Structural Equation Modelling (SEM) to model the factors that influenced youth to become addicted to profane media content.

Results: The most preferred genre among students is football, at 49.5%, followed by news, 12.5%, and comedy, 10%. WhatsApp, at 43%, is the most preferred platform among 73% subscribers of streaming services. As far as content preference goes, adult content is the most preferred at 44.5%, followed by movies at 34%, while web series is the least preferred at 4% only.

Conclusion: The study concluded that football is the most favored genre among students who watch television daily. The study concludes that media content significantly contributes to the promotion of social vices. The study recommends that media regulatory boards should implement stricter regulations to monitor and control the broadcast of explicit and harmful media content, particularly on streaming platforms and television.

Keywords: mass media, social vices, media content, social media.

1. INTRODUCTION

Social media's innovation resides in its capacity to democratize media creation and dissemination, allowing persons without prior access to broadcast media to engage actively on a significant scale (Gil de Zúñiga et al., 2018). The intentional use of media tools to enhance individual and communal expressiveness exacerbates this problem. Traditional home movies had a restricted audience unless selected for broadcasts such as America's Funniest Home Videos; however, platforms like YouTube now enable anybody with a smartphone and internet access to disseminate content worldwide (Moreira Aguirre et al., 2018). Research highlights that social media enhances political speech and democratizes communication by offering wider access and novel participatory avenues for citizens (Gil de Zúñiga et al., 2018). This shift signifies a substantial change in media dynamics, enabling non-traditional content makers to impact public conversation and participation (Barberá&Zeitzoff, 2018). What is placed online may not be visible to everyone, but when people choose to share content via spreadable media, it appears to go viral, generating millions of views in a short period of time (Jenkins, Ford, & Green, 2013).

UNDER PEER REVIEW

In any community, the media is known to serve three main functions: to inform, educate, and amuse (Akoja, 2016). However, in recent years, these responsibilities have become somewhat misplaced, with profane programs producing moral turmoil in societies. The three nested and interconnected modes of sociality are information (cognition), communication, and cooperation (Hofkirchner, 2013). Every type of media is an information technology; they give humans information. As social truths, this data enters the human domain of knowledge and shapes thought. Books, newspapers, journals, posters, flyers, films, television, radio, CDs, and DVDs are all examples of information media (Fuchs, 2014). Asante (1997) underlined that the mass media play a critical role in engendering growth among the public in any developing country. He believes that the media should play an important role in the difficult job of nation-building and modernization.

Humans can only exist if they form social bonds with other people. In these relationships, they communicate by exchanging symbols. In every social interaction, a human being externalizes aspects of his or her knowledge. As a result, this information has an impact on others, who change portions of their knowledge structures and, as a result, externalize parts of their own knowledge, resulting in the differentiation of the first individual's knowledge (Fuchs, 2014). The power of social networking sites grows in direct proportion to their functions. Therefore, their popularity and reach have a significant impact on users' attitudes and perceptions of them. It is undeniable that social networking and social media have a significant impact on how individuals think and act (Olga Pilli, 2015). People claim that all media are social under sociological theory since they are a part of society and aspects of it are present in the technological artifacts we use (Fuchs, 2014). The unflinching desire of the youth to be integrated into the media space (traditional and social media) and their inquisitiveness to wrap themselves around every facet of it expose them to dangerous habits garnered from the media.

Our society's moral decay has reached a point where it is a cause for concern (Abba, 2015). Young people and future leaders show no respect for their elders. They engage in a wide range of antisocial behaviors that are harmful to society. Any society that is not morally healthy is doomed to face many societal threats. Our religion, culture, and traditions embody our moral principles. However, our kids are not very religious for several reasons. As a result, people are lining up to embrace digital culture in its entirety, forsaking our indigenous culture and heritage in the process and therefore losing their identity.

Music videos, lyrics, the internet, and periodicals all have an impact on our behavior and reactions. The media's portrayal of morality is not and will not be moral. Anyone who relies on sources, such as a magazine featuring abnormally thin models, would regard such models as "perfect," creating a false sense of beauty and life (Nesi and Prinstein, 2015). Young people are enticed to watch and read through social media because they are swept up in what they believe everyone else is doing, and they feel compelled to follow suit (Gross, 2004). No one is secure on social media, according to Bonaya (2015), because some people use it to disseminate rumors, reveal sexual images, or simply mock celebrities.

Recently, a multitude of nude films and photographs have flooded the media, a phenomenon that was astonishingly absent previously. As a result, it has fueled youth sexual longing, which has led to an increase in defilement cases, with 1,270 reported in 2019 (Ako, 2021). Unfortunately, Ghana is the world's second-most-watched porn country, according to Pornhub (2020). This follows a survey conducted by the world's biggest pornographic websites, which revealed that countries claiming to be religious have high numbers of people watching sexually explicit items on a regular basis (Flewellen et al., 2021). Many young people's desire to view porn is based on their progressive exposure to the extensive availability of sexual content videos and images in the media, which has led them to seek out pornography websites to satisfy their insatiable lust.

While a lot of research has been done on social media use, there is a big hole in the research when it comes to the specific reasons why young people are addicted to profane media content, how that content promotes social vices, and the shows that young people like to watch. While numerous studies have explored students' attitudes toward established learning platforms like Facebook, there is a growing need to delve into the underlying causes of youth addiction to inappropriate media content, posing critical questions for both researchers and users in anticipating the future trajectory of social networking sites and their societal and moral implications (Archambault and Grudin, 2012; Johnston et al., 2013; Michikyan et al., 2015).

Consequently, this article explored the factors that influence the youth to become addicted to profane media content, the role of media content in promoting social vices, and the programs most cherished by the youth in the media. By addressing this gap in research, we aim to contribute valuable insights into the dynamics of media consumption among the students and its potential consequences on their ethical values.

2. MATERIAL AND METHODS

RESEARCH DESIGN

The researchers used a cross-sectional study design. Cross-sectional studies are useful for determining the prevalence of a behavior in a population at a specific time (Sedgwick, 2014). The researchers were able to collect data on the variables that cause youth to become hooked on profane media content, the role of media content in promoting social vices, and the most popular media programs among teenagers. Because of its potential to collect both qualitative and quantitative information in its natural habitat, the design was a method of choice and was the most appropriate for this research (Blair et al., 2019).

UNDER PEER REVIEW

POPULATION

In the process of sample selection, researchers selected 242 undergraduate students from the various faculties of the university.

STUDY POPULATION

In general, every research study begins with the researchers embarking on a trip to better understand a phenomenon. This journey necessitates the collection of data from respondents, in this case, Tamale Technical University students, at some stage. Students at Tamale Technical University in the Northern Region of Ghana make up the study's population. This means that the respondents were chosen based on their possessing the relevant characteristics relating to the topic under study.

SAMPLE SIZE DETERMINATION

The sample size was determined on the students of the Tamale Technical University in the study. To determine the sample size for large populations, we use the Cochran approximation which is stated as below:

$$n = \frac{n_o}{1 + \frac{n_o}{N}}$$

$$n_o = \frac{Z^2_{a/2} PQ}{d^2}$$

n= sample size
N=Population Size
p = proportion of students who are male
q = proportion of students who are female

Z= the value that specifies the level of confidence usually is 95%, for surveys in which

case z is set to 1.96

d= the degree of accuracy = 0.05

Substituting the above figures into the mentioned formula:

$$n_o = \frac{(1.96)^2(0.7)(0.3)}{(0.05)^2} = 323$$

$$n = \frac{323}{1 + \frac{323}{980}} = 242$$

list 1: Distribution of students by faculty

Faculty	Population	Sample Selected
Faculty of Applied Sciences & Technology	80	20
Faculty of Engineering	45	11
Faculty of Allied Health and Pharmaceutical Science	40	10
Faculty of Business Studies	350	90
Faculty of Creative Arts & Technology	330	84
Faculty Agriculture & Natural Resources	85	22
Faculty of Built and Natural Environment	50	13
Total	**980**	**242**

Source:TaTU student enrollment records (2024)

SAMPLING TECHNIQUE

We selected the sample using the stratified sampling approach. We chose this sample process due to its scientific nature, objectivity, and lack of personal bias. The researchers used this method to categorize Tamale Technical University students into the following faculties: Faculty of Creative Arts & Technology, Faculty of Applied Sciences and Technology, Faculty of Business Studies, Faculty of Built and Natural Environment, Faculty of Engineering, Faculty of Allied Health and Pharmaceutical Science, and Faculty of Agriculture & Natural Resources. Following the stratification, a proportion of

UNDER PEER REVIEW

students were randomly selected from the various faculties using simple random selection, based on the number of students in each category.

DATA COLLECTION INSTRUMENT/TECHNIQUES

This study collected primary data. We used a standardized questionnaire to collect quantitative data from the respondents. We designed the questionnaire around the study's aims, incorporating both closed-ended and open-ended questions. The questionnaire was designed to gather information on the most frequently viewed media materials and their impact on Ghanaian youths' moral constructs. Data collection was subjected to stringent controls, and processes were strictly followed to guarantee that the data collected was accurate, reliable, and valuable (Knapp & Mueller, 2010).

During data collection, the researchers gave the respondents the questionnaire and instructed them on how to answer it. The researchers monitored the exercise and made sure respondents complied and answered the entire question, which helped reduce the chance of the evaluator's bias. The researchers self-administered the questionnaire, repeating this procedure until they achieved the required sample size.

DATA ANALYSIS

The descriptive analysis, such as percentages and central tendencies (means, mode) and dispersion (standard deviation), was used to explore the programs most cherished by the youth in the media. We used the Relative Importance Index (RII) to pinpoint the specific role of media content in fostering social vices. We used Structural Equation Modeling (SEM) to model the factors that lead youth to develop an addiction to profane media content, enabling better inference.

MODEL SPECIFICATION

Structural equation modelling (SEM)

According to Khan and Adil (2013), selecting an appropriate method of statistical analysis requires taking into account a number of different aspects. Some of these elements include the study challenge, the aims of the research, the properties of the data (normal and nonnormal), and the essential components of the statistical approaches. The study's hypothesis says that seven latent constructs, which are external variables, have a direct effect on the moral behavior of students. These constructs can be broken down into two groups: those that have a positive influence and those that have a negative influence. Consequently, we conducted inferential and model fit analyses. It was decided to use structural equation modeling (SEM), a group of statistical methods, because it can look at the relationships between different concepts at the same time, according to Tabachnick and Fidell (2007).

The measurement model specifies how latent variables are measured by observed variables.

Equation for Observed Variables:

$$\boldsymbol{y} = \boldsymbol{\Lambda_y \eta} + \boldsymbol{\epsilon} \qquad \textbf{(1)}$$

y: A vector of observed variables. These are the actual data points measured directly through surveys, experiments, or other means.

$\boldsymbol{\Lambda_y}$: The factor loading matrix. This matrix contains coefficients that show the relationship between the latent variables (η) and the observed variables (y). Each element in this matrix represents the extent to which a latent variable influences a particular observed variable.

$\boldsymbol{\eta}$: A vector of latent variables. These are unobserved variables that are inferred from the observed variables and are thought to represent underlying constructs.

$\boldsymbol{\epsilon}$: A vector of measurement errors or residuals. These represent the part of the observed variables that is not explained by the latent variables, including random errors and other factors not captured by the model.

Equation for Exogenous Variables:

$$\boldsymbol{x} = \boldsymbol{\Lambda_x \xi} + \boldsymbol{\delta} \qquad \textbf{(2)}$$

$\boldsymbol{x}$: A vector of observed exogenous variables. These are the observed variables that are presumed to influence other variables in the model but are not influenced by other variables within the model.

$\boldsymbol{\Lambda_x}$: The factor loading matrix for the exogenous variables. This matrix contains coefficients that represent the relationship between the latent exogenous variables (ξ) and the observed exogenous variables (x). Each element in this matrix indicates how much a particular latent variable influences an observed variable.

$\boldsymbol{\xi}$ A vector of latent exogenous variables. These are unobserved variables that represent underlying constructs presumed to be the cause of variations in the observed exogenous variables.

UNDER PEER REVIEW

$\boldsymbol{\delta}$: A vector of measurement errors or residuals associated with the exogenous variables. This accounts for the part of the observed exogenous variables that is not explained by the latent exogenous variables, including random errors and other unmeasured factors.

COVARIANCE

The covariance structure in SEM defines the relationships among the error terms and latent variables.

1. Covariance of Errors:

$$\mathbf{Cov}(\boldsymbol{\epsilon}) = \boldsymbol{\Theta_\epsilon}$$

$$\mathbf{ov}(\boldsymbol{\delta}) = \boldsymbol{\Theta_\delta}$$

2. Covariance of Latent Variables

$$\text{Cov}(\xi) = \Phi$$

3. Covariance of Structural Errors:

$$\text{Cov}(\zeta) = \Psi$$

Θ_ϵ and Θ_δ are matrices representing the covariances of the measurement errors.

Φ is a matrix representing the covariances among the exogenous latent variables

Ψ is a matrix representing the covariances among the structural errors.

FIT INDICES

Fit indices in SEM assess the goodness of fit of the model

Chi-Square Statistic:

$\chi^2 = N \times \text{FML}$

- N Is the sample size.
- Fml is the maximum likelihood fitting function.

Root Mean Square Error of Approximation (RMSEA)

$$\text{RMSEA} = \sqrt{\frac{\chi^2 - \text{df}}{N \times \text{df}}}$$

Df is the degrees of freedom.

Comparative Fit Index (CFI):

$$\text{CFI} = 1 - \frac{(\text{model})}{(\text{baseline})}$$

FML(baseline) refers to the fitting function of the baseline model.

MISSING DATA

We scrutinized the data for missing responses before conducting a comprehensive analysis, as these omissions adversely affect the SEM outcomes. Kline (1998) identifies three methods for addressing concerns of missing data. We employ casewise deletion to ensure consistency, analyzing only cases with complete records. The second method is pairwise deletion, which involves the elimination of missing replies for constructs throughout a particular calculation as necessary. For the third strategy, imputation, patterns are looked at, and a score from another case with a similar profile across other variables is used to fill in a missing observation (Kline, 1998). Recently, more inventive methods have been utilized to tackle the problem of missing data, including Maximum Likelihood Estimation (MLE). This study saw minimal concerns with missing data, as Google Forms was mostly utilized for questionnaire distribution.

UNDER PEER REVIEW

3. RESULTS AND DISCUSSION
RESULT

Participants completed and returned 200 of the 242 questionnaires distributed through Google Forms, yielding a response rate of approximately 82.6%. This signifies a considerable degree of participation within the target demographic, as more than eighty percent of respondents contributed their feedback. Conversely, this indicates that 17.4% of the surveys remained unanswered.

Table 1: Demographic characteristics of students of Tamale Technical University

Question	Response Category	Frequency	Percent
Age	16-20	45	22.5
	21- 26	80	40.0
	27 – 31	63	31.5
	32+	12	6.0
	Total	**200**	**100.0**
Gender	Female	72	36.0
	Male	128	64.0
	Total	**200**	**100.0**
Academic level	Level 100	75	37.5
	Level 200	67	33.5
	Level 300	32	16.0
	Level 400	26	13.0
	Total	**200**	**100.0**
Place of residence	Family or relatives' home	29	14.5
	Off-campus apartment or rental	14	7.0
	On-campus Hall	123	61.5
	Shared housing with friends or roommates	34	17.0
	Total	**200**	**100**

Table 1 indicates that the majority age category among students is 21-26 years, comprising 40%, whilst students aged 32 and above constitute the smallest demographic at 6%. The gender breakdown indicates a greater percentage of male pupils (64%) relative to female students (36%). Level 100 comprises the largest proportion of pupils at 37.5%, while Level 400 accounts for the smallest amount at 13%. A majority of students (61.5%) reside in on-campus dormitories, demonstrating a pronounced preference for university accommodation. Conversely, merely 7% of students inhabit off-campus apartments or rentals, making it the least prevalent accommodation option.

Table 2: Television Programs Cherished by students

Television Viewing Frequency	Frequency	Percent
Daily	112	56.0
Never	7	3.5
Once a week	23	11.5
Rarely	12	6.0
Several times a week	46	23.0
Total	**200**	**100.0**
Most Appealing Television Genre		
Comedy	20	10.0

UNDER PEER REVIEW

Television Viewing Frequency	Frequency	Percent
Documentaries	17	8.5
Drama	6	3.0
Football	99	49.5
Politics	19	9.5
News	25	12.5
Reality shows	14	7.0
Total	**200**	**100.0**

Table 2 illustrates the television viewing patterns of the respondents. The results indicate that the majority of students (56%) engage in daily television viewing, establishing it as the predominant frequency. Conversely, a minor proportion (3.5%) indicates that they never engage in television viewing. Individuals who watch many times weekly comprise 23%, while 11.5% engage in viewing once a week, and 6% do so infrequently. In terms of favored television genres, football is predominantly the most popular, captivating nearly half (49.5%) of participants. News attracts 12.5% of responders, while comedy and politics garner 10% and 9.5%, respectively. The least preferred genres include drama (3%) and reality shows (7%), reflecting varied tastes but a pronounced predilection for sports, especially football.

Table 3: Streaming Services and Online Content

Streaming Service Subscription Status	Frequency	Percent
No	54	27.0
Yes	146	73.0
Total	**200**	**100.0**
Most Used Streaming Platform	**Frequency**	**Percent**
Amazon Prime Video	5	2.5
Chrome	22	11.0
Hulu	1	0.5
Netflix	18	9.0
TikTok	45	22.5
WhatsApp	86	43.0
YouTube	23	11.5
Total	**200**	**100.0**
Preferred Content Type on Streaming Services		
Adult content	89	44.5
Documentaries	17	8.5
Movies	68	34.0
TV shows	18	9.0
Web series	8	4.0
Total	**200**	**100.0**

A vast majority of respondents (73%) subscribe to a streaming service, whereas 27% do not subscribe to any streaming service, as seen in the result presented in table 3 on the utilization of streaming services. The most popular streaming platform is WhatsApp, which has a usage rate of 43%, followed by TikTok, which has a usage rate of 22.5%, and Hulu, which has the lowest usage. YouTube and Chrome are also popular choices, with 11.5% and 11% of respondents using them, respectively, from the pool of respondents. Adult content is the most favored material among respondents, with 44.5% selecting it. On the other hand, web series are the type of content that is least preferred, as it is only appealing to 4% of respondents. In addition, movies are quite popular, with 34% of the respondents citing them as their preferred content category.

UNDER PEER REVIEW

Table 4: Relative Importance Index ofthe role of media content in promoting social vices

Role of media content	Score
Social media can be a platform for promoting social vices such as fraud.	0.801
Social media has the potential to influence our moral judgments and behaviors.	0.772
Media content, including social media, can lead to the glamorization of harmful behaviors.	0.828
Exposure to media content containing explicit or adult material can negatively affect moral reasoning.	0.853
The portrayal of sexual content in media can promote sexual objectification.	0.763
Media content, including social media, can contribute to the normalization of harmful behaviors.	0.812

The Relative Importance Index (RII) scores show that participants think that seeing explicit or adult content (RII = 0.853) and making bad behaviors look cool (RII = 0.828) are the main ways that media content promotes social vices. This shows a strong concern that this kind of content could hurt moral thinking and maybe even make bad behaviors seem normal (RII = 0.812). At the same time, the role of social media in encouraging bad behaviors like fraud (RII = 0.801) and shaping moral judgments (RII = 0.772) is seen as important, albeit not as crucial. The lowest score is for sexual content that leads to objectification (RII = 0.763), which means that it is seen as less of a factor in promoting social vices than other factors.

Exploratory factor analysis on positive influences of social media

Table 5: Communalities and reliabilities forpositive influences of social media

Communalities

	Initial	Extraction
Exposure to positive moral messages on social media can contribute to the moral development of students	1.000	.634
I feel close to my friends and loved ones when using social media websites.	1.000	.548
The use of social media websites has made me maintain my old relationship with friends.	1.000	.509
Social media websites have improved my social and moral behavior towards society.	1.000	.660
Social media can promote positive character traits such as humor, appreciation of beauty, creativity, love, and courage, which are beneficial for the moral development of students	1.000	.423
Responsible use of social media platforms can lead to the promotion of ethical behavior among tertiary students.	1.000	.451

UNDER PEER REVIEW

Social media can be used as a tool to educate and raise awareness about the importance of moral values and ethical behavior.	1.000	.495

KMO andBartlett'sTest		
Kaiser-Meyer-OlkinMeasure of Sampling Adequacy.		.780
Bartlett's Test of Sphericity	Approx.Chi-Square	440.4613
	Df.	21
	Sig.	.000
Cronbach's alpha		.870

We performed a Principal Component Analysis (PCA) on a total of seven positively influencing factors associated with social media. The Kaiser-Meyer-Olkin (KMO) test produced a result of .780, which was greater than the threshold of 0.5. Based on this result, it can be concluded that the sample size for this investigation is sufficient. Table 5 reveals that the Bartlett's test of sphericity yielded a statistically significant chi-squared value of 440.4613. Additionally, the associated significance level (Sig.) was .000, which suggests that the data are suitable for principal components analysis. For the exploratory factor analysis (EFA), a significant value of less than 0.05 is not acceptable because the data does not form an identity matrix. As a result, there is no association between the variables, as stated by George and Mallery (2003). An internal consistency and reliability of the study instrument was found to be quite high, as indicated by the Cronbach's alpha value of .870 that was recorded. The values that were reported from the communalities table ranged from .40 to .70, which is in line with the research that Costello and Osborne (2005) conducted. These values indicate the appropriateness of the variables measuring the positive influence of social media.

Table 6: Total varianceexplained and pattern matrix forpositive influences of social media

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**	Total	% of Variance	**Cumulative %**
1	3.320	47.432	47.432	3.320	47.432	47.432
2	0.989	14.131	61.564			
3	0.789	11.266	72.829			
4	0.682	9.744	82.574			
5	0.575	8.217	90.791			
6	0.383	5.468	96.259			
7	0.262	3.741	100.000			

	Component				
	1	2	3	4	5
Exposure to positive moral messages on social media can contribute to the moral development of students.	.796				
I feel close to my friends and loved ones when using social media websites.	.740				
The use of social media websites has made me maintain my old relationship with friends.	.714				

UNDER PEER REVIEW

Social media websites have improved my social and moral behavior towards society.	.812
Social media can promote positive character traits such as humor, appreciation of beauty, creativity, love, and courage, which are beneficial for the moral development of students.	.650
Responsible use of social media platforms can lead to the promotion of ethical behavior among tertiary students.	.593
Social media can be used as a tool to educate and raise awareness about the importance of moral values and ethical behavior.	.442

Table 6 shows the total variance that can be explained. One positive impact of the social media factor with eigenvalues above 1 led to 3.320 and explains 47.432% of the variance.

Exploratory factor analysis on negative influences of social media

Table 7: Communalities and reliabilities fornegative influences of social media

Communalities		
	Initial	Extraction
The social media websites have changed my ethics and my relationship with others negatively.	1.000	.770
Tertiary students have personally experienced situations where social media influenced their moral decision-making negatively.	1.000	.514

UNDER PEER REVIEW

Students feel pressured to conform to certain moral standards depicted on social media.	1.000	.546
Morally questionable content on social media contributes to a decline in moral values among tertiary students.	1.000	.632

KMO andBartlett'sTest		
Kaiser-Meyer-OlkinMeasure of Sampling Adequacy.		.621
Bartlett's Test of Sphericity	Approx.Chi-Square	343.286
	Df.	6
	Sig.	.000
Cronbach's alpha		.790

We used Principal Component Analysis (PCA) to examine four detrimental effects of social media. The KMO test produced a result of .621, above the .5 cutoff. This figure demonstrates that the sample size was sufficient for this investigation. With a high chi-squared value of 343.286 and a very low significance level (Sig.) of.000, Table 7 shows that Bartlett's test of sphericity showed that the data was suitable for NI. Since the data does not produce an identity matrix, a significant value of less than .05 is unsuitable for NI; hence, there was no correlation between the variables (George & Mallery, 2003). A Cronbach's alpha of .790 was found, indicating that the research instrument has a satisfactory level of internal consistency and reliability. Values from the communalities table ranged from .40 to .70, which is consistent with Costello and Osborne's (2005) research. These numbers show that the factors evaluating the detrimental effects of social media are appropriate.

Table 8: Total varianceexplained and pattern matrix fornegative influences of social media

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**	Total	% of Variance	**Cumulative %**
1	2.463	61.565	61.565	2.463	61.565	61.565
2	.933	23.325	84.890			
3	.426	10.642	95.531			
4	.179	4.469	100.000			

	Component				
	1	2	3	4	5
The social media websites have changed my ethics and my relationship with others negatively	.796				
Tertiary students have personally experienced situations where social media influenced their moral decision-making negatively	.740				
Students feel pressured to conform to certain morazl standards depicted on social media.	.714				

UNDER PREVIEW

Morally questionable content on social media contributes to a decline in moral values among tertiary students	.812

Based on the overall variation that is explained in Table 8, a single negative influence of social media factor with eigenvalues greater than one resulted in 2.463, which accounts for 61.565% of the variance.

Test for normality of data

A major component of this research involved doing a normality test for the data, which was essential in selecting the statistical analysis approach of SEM. The initial stage involved assessing the normality of the data with the Shapiro-Wilk normality test. Ghasemi and Zahediasl (2012) assert that the Shapiro-Wilk normality test is typically employed to assess data normality when the sample size is less than 2000 in a research study. Another main goal of the Shapiro-Wilk normality test is to find out if the data is parametric or non-parametric. This is important because it affects the analysis method that is used (Cassel et al., 1999). The Shapiro-Wilk normality test indicated that the variables were non-parametric since all measurement variables yielded a value of 0.000, which is below the 0.05 threshold for normality. Therefore, a non-parametric method like PLS-SEM was appropriate compared to the parametric approach of CB-SEM. Table 9 presents the details of the Shapiro-Wilk normalcy test.

Consequently, a non-parametric method like PLS-SEM was more appropriate compared to the parametric approach of CB-SEM.

Table9:Testfor normalityofdata

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
Positive influences (PI)						
Exposure to positive moral messages on social media can contribute to the moral development of students	.331	197	.000	.728	197	.000
I feel close to my friends and loved ones when using social media websites.	.325	197	.000	.767	197	.000
The use of social media websites has made me maintain my old relationship with friends.	.238	197	.000	.867	197	.000
Social media websites have improved my social and moral behavior towards society.	.302	197	.000	.831	197	.000
Social media can promote positive character traits such as humor, appreciation of beauty, creativity, love, and courage, which are beneficial for the moral development of students	.296	197	.000	.750	197	.000
Responsible use of social media platforms can lead to the promotion of ethical behavior among tertiary students	.285	197	.000	.706	197	.000

Social media can be used as a tool to educate and raise awareness about the importance of moral values and ethical behavior.	.285	197	.000	.744	197	.000
Negative Influences (NI)						
The social media websites have changed my ethics and my relationship with others negatively	.288	200	.000	.833	200	.000
Tertiary students have personally experienced situations where social media influenced their moral decision-making negatively	.276	200	.000	.752	200	.000
students feel pressured to conform to certain moral standards depicted on social media.	.258	200	.000	.739	200	.000
Morally questionable content on social media contributes to a decline in moral values among tertiary students	.307	200	.000	.811	200	.000

We evaluated the normality of the data using the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk tests for both positive and negative effects of social media. For both the K-S and Shapiro-Wilk tests, all of the variables that were looked at had p-values below 0.05 (Sig. =.000), which means that they were significantly different from a normal distribution. The Shapiro-Wilk test statistics are between 0.706 and 0.867, while the K-S test statistics are between 0.238 and 0.331 for positive influences and between 0.258 and 0.307 for negative influences. This shows that the data is not normally distributed. Consequently, all variables in both the positive and negative effect categories violate the premise of normality.

Partial least squares - structural equation modelling (PLS-SEM)

This research employed PLS-SEM to evaluate the significance and overall effects of both positive and negative influences of social media on students' moral behavior.

Table 10: Model fit test

User Model versus Baseline Model	
Comparative Fit Index (CFI)	.933
Tucker-Lewis Index (TLI)	.930

The Comparative Fit Index (CFI) of .933 and the Tucker-Lewis Index (TLI) of 0.930 demonstrate an excellent fit of the user model relative to the baseline model. Both values are higher than the commonly accepted threshold of.90, which means that the user model greatly improves the baseline model's ability to explain the data. The fact that the CFI value is close to.95 and the TLI value is higher than.90 shows that the model fits well and captures the relationships between the variables. The results indicate that the user model accurately represents the data, requiring minimum modifications.

list 2: Loglikelihood and Information Criteria

Loglikelihood user model (H0)	-2372.765
Loglikelihood unrestricted model (H1)	-2126.278
Akaike (AIC)	4791.530
Bayesian (BIC)	4867.043
Sample-size adjusted Bayesian (SABIC)	4794.180

The log-likelihood and information criterion values obtained provide a better understanding of the model's complexity and fit. There is a higher chance that the unrestricted model (H1) is correct than the user-specified model (H0), with a log-likelihood of -2372.765. This means that the unrestricted model fits the data better. The Akaike Information Criterion (AIC) is 4791.530, the Bayesian Information Criterion (BIC) is 4867.043, and the sample-size adjusted BIC (SABIC) is 4794.180. Both of these criterion values point to the same conclusion. It is generally accepted that a better model fit is indicated by lower values of these criteria in comparison to other models that have similar data.

UNDER PEER REVIEW

Table 11: Parameter Estimates of the influence of social media factors on behavior

Latent Variables

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Positive Influence						
PI1	1.000				0.600	0.714
PIE	0.943	0.113	8.329	0.000	0.566	0.641
PI3	1.123	0.129	8.681	0.000	0.673	0.669
PI4	1.330	0.126	10.574	0.000	0.798	0.832
PI5	0.684	0.090	7.589	0.000	0.410	0.583
PI6	0.585	0.095	6.181	0.000	0.351	0.473
PI7	0.593	0.122	4.869	0.000	0.356	0.372
Negative Influence						
NI1	1.000				0.860	0.883
NI2	0.473	0.071	6.660	0.000	0.407	0.464
NI3	0.418	0.061	6.851	0.000	0.360	0.476
NI4	0.945	0.062	15.367	0.000	0.813	0.896

These observable variables (PI1, PIE, PI3, PI4, PI5, PI6, and PI7) are all important for measuring the latent variable Positive Influence, but they are all important in different ways. PI4's high loading of 0.832 indicates a strong link to the latent construct. This means that it is a major sign of positive influence. On the other hand, PI7, which has a standardized loading of 0.372, has a weaker correlation, which indicates that it captures less variance in positive influence in comparison to other indicators. The *P*-values (*P*(>|z|)) indicate that all of the estimates for the variables that fall under the category of Positive Influence are statistically significant at the .000 level. This suggests that each observed variable makes a significant contribution to the process of identifying the latent factor when taken into consideration. The z-values also demonstrate that the associations are significantly different from zero, with PI4 displaying the greatest z-value, 10.574, which highlights the significant influence that it has.

There is a high loading of 0.883 for the Negative Influence latent variable, which indicates that NI1 is the most powerful indication of Negative Influence in the model. A considerable loading of 0.896 is also associated with NI4, which highlights the significance of this concept in terms of its definition. On the other hand, the loadings of the two indicators, NI2 and NI3, are slightly lower, coming in at 0.464 and 0.476, respectively. This indicates that they have moderate connections with influence that is negative. Each path that leads from Negative Influence to its observed variables is statistically significant, with *P*-values of .00, just like the paths that lead from Positive Influence. This means that the relationships are strong. *P*-values of .000, which indicates that the relationships are strong. The normalized estimates and high z-values offer additional evidence, confirming the validity of the indicators in assessing negative influence. Among the indicators, NI4 has the highest z-value of 15.367, which highlights the significant contribution it makes to the latent variable.

Table 12: Results of Regression analysis

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Negative Influence						
Positive Influence	1.139	0.125	9.139	0.000	0.794	0.794

The regression analysis reveals a significant positive relationship between Positive Influence and the dependent variable, Negative Influence. The calculated coefficient for Positive Influence is 1.139, accompanied by a standard error of 0.125, yielding a z-value of 9.139 and a *P*-value of .000. The low *P*-value (< .05) indicates that the impact of Positive Influence on Negative Influence is statistically significant.

Table 13: Results of Variances

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.PI1	0.346	0.041	8.428	0.000	0.346	0.490
.PIE	0.458	0.051	8.925	0.000	0.458	0.589
.PI3	0.558	0.064	8.760	0.000	0.558	0.552
.PI4	0.283	0.042	6.674	0.000	0.283	0.308
.PI5	0.326	0.036	9.192	0.000	0.326	0.660
.PI6	0.427	0.045	9.516	0.000	0.427	0.776
.PI7	0.788	0.081	9.698	0.000	0.788	0.862
.NI1	0.210	0.039	5.446	0.000	0.210	0.221
.NI2	0.602	0.063	9.629	0.000	0.602	0.784
.NI3	0.442	0.046	9.610	0.000	0.442	0.774
.NI4	0.162	0.033	4.910	0.000	0.162	0.197
Positive Inflnc	0.360	0.066	5.477	0.000	1.000	1.000

UNDER PEER REVIEW

Negative Inflnc	0.273	0.049	5.518	0.000	0.369	0.369

The variances table shows that all the variables and latent constructs in the model have z-values above the standard level of 1.96 and *P-values* of.000, which means that the variances are statistically significan*t.* The variances for the Positive Influence indicators (PI1 to PI7) range from .283 to .788, while the standardized loadings (Std.all) vary from 0.308 to 0.862. PI7 exhibits the highest standardized loading of 0.862, signifying it as the most strongly correlated indicator for Positive Influence, whilst PI4 displays the lowest loading at 0.308. The Negative Influence indicators (NI1 to NI4) exhibit variances ranging from .162 to .602, accompanied by standardized loadings between .197 and .784. NI2 demonstrates the highest standardized loading of .784, rendering it the most significant signal for Negative Influence, while NI4 exhibits the lowest at .197. The latent constructs have variances of .360 for Positive Influence and .273 for Negative Influence, both of which are highly significant, with normalized variances of 1.000 and 0.369, respectively. Positive Influence demonstrates complete standardization for identification, while Negative Influence displays a significant degree of variance.

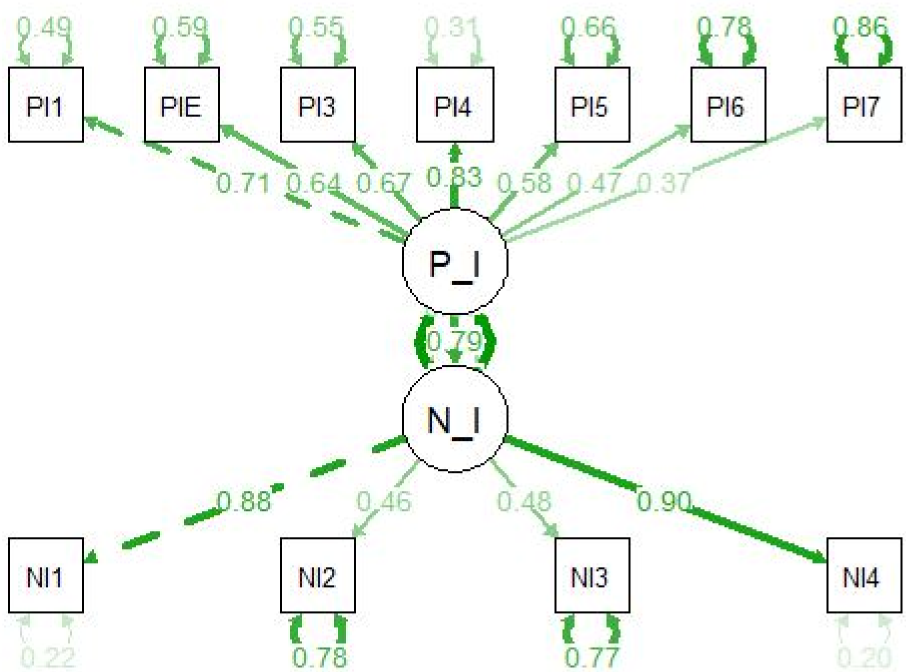

Figure 1: Structural Equation Model (SEM) Path Diagram of Positive and Negative Influences of Social Media

The Structural Equation Model (SEM) path diagram shows the links between two hidden variables, Positive Influence (PI) and Negative Influence (NI), and the observable variables that go with them. Seven indicators (PI1, PIE, PI3, PI4, PI5, PI6, and PI7) are used to assess the latent variable Positive Influence, whereas four indicators (NI1, NI2, NI3, and NI4) are used to evaluate Negative Influence. A standardized factor loading, which indicates the degree of correlation between the observed variable and the latent variable, is assigned to each path from the latent variable to its indicators. While PI7 has a weaker relationship, PI4 has a high loading (.83) on Positive Influence, which means it accurately represents this hidden idea. For instance, social media websites have improved my moral and social behavior toward society (PI4).

A curved two-headed arrow with a value of.79 connects the two latent variables to show the relationship between Positive Influence and Negative Influence. This shows a strong positive correlation. This indicates that an increase in the perception of positive influences correlates with a rise in the perception of negative influences. The Negative Influence variable shows that the item "social media websites have negatively affected my ethics and relationships with others" (NI1) has a strong link (loading of.88), but NI2, NI3, and NI4 have slightly lower loadings, which means they make different contributions to the latent construct.

Discussion

Research by Čerepinko et al. (2020), which examines television's adaptability to streaming-dominated contexts, reveals television's continuous significance, particularly for sports. It shows a change toward viewership that is specialized to certain material, like sports or visually stimulating genres. Similar to this, Mosharafa (2019) notes the growing popularity of digital and social media platforms like YouTube and WhatsApp while confirming that young people have preferences for particular television genres. While this is consistent with WhatsApp's observed predominance in the current study, it also draws attention to variations in platform integration and genre preferences. Sobral (2019), on the other hand, talks about the fall in linear television and highlights the move to binge-watching and digital-first consumption. These results imply that while television continues to play a vital role, it is becoming more and more entwined with digital activities.

Merrill and Liang (2019), who look at connections between media exposure and risky behaviors, agree with what this study says about how streaming services and social media can make people do bad things. These links are less significant than those found in peer pressure, they say. Furthermore, Chan et al. (2022) draw attention to how streaming services like Netflix impact behavioral patterns that are motivated by social connection and amusement. The study's focus on how explicit information affects moral reasoning brings up concerns about exposure to harmful content. This is in line with Zikarge's (2019) findings on the media's dual role in shaping teenage behavior. Sahoo's (2024) results agree with those of Sobral (2019) and Zdanowicz et al. (2020) in that they show how family and community can help balance out the effects of screen time. Sahoo says that streaming services can expose kids to inappropriate content, but parental supervision can help protect them. This is similar to Sobral and Zdanowicz's point that having a supportive family and community can lessen the bad effects of spending more time in front of a screen.

4. CONCLUSION AND RECOMMENDATIONS

The study concludes that both television and streaming services significantly impact the consumption of youth media. The most preferred genre among students is football, at 49.5%, followed by news, 12.5%, and comedy, 10%. WhatsApp, at 43%, is the most preferred platform among 73% subscribers of streaming services. As far as content preference goes, adult content is the most preferred at 44.5%, followed by movies at 34%, while web series is the least preferred at 4% only. The study concludes that media content significantly contributes to the promotion of social vices. Respondents identified the glamorization of harmful behaviors (RII = .828) and exposure to explicit or mature material (RII = .853) as the most influential factors. The content in question is of significant concern due to its potential to have a detrimental effect on moral reasoning and to normalize harmful behaviors (RII = .812). Also, the role that social media plays in making vices like fraud easier to do (RII =.801) and the impact of moral judgments (RII =.772) is seen as important, albeit a little less critical. The least important factor was the portrayal of sexual content that leads to objectification (RII =.763). This means that people think it is not as important as other factors in encouraging social vices.

The Structural Equation Model (SEM) path diagram, which shows the connections between Positive Influence (PI) and Negative Influence (NI), shows that social media has a big effect on how students act. The statement "social media websites have improved my social and moral behavior towards society" (PI4) demonstrates a significant relationship with a standardized factor loading of .83, and Positive Influence is measured through seven indicators. Conversely, an additional indicator (PI7) exhibits a weakened correlation with a loading of .37. This implies that, although social media can have a beneficial effect on the social and moral behavior of students, the extent of this influence is contingent upon the specific aspects of their experiences.

From this study, we recommend that government and media regulatory boards implement stricter regulations to monitor and control the broadcast of explicit and harmful media content on television and streaming platforms. Tertiary institutions should introduce curriculum-based media literacy courses to help students critically evaluate the impact of media on their behavior and values.

CONSENT

For this research, we distributed a self-administered, structured questionnaire via Google Forms to collect the data. We exclusively dedicated the data collection procedure to obtaining respondents' perspectives on their media consumption patterns, preferences, and perceived effects. The participants' participation was wholly voluntary, anonymous, and did not present any foreseeable risks. The study did not involve any invasive procedures or interactions that could cause damage, nor did it involve any sensitive or personal data that could identify individual respondents. As such, it adhered to standard practices for low-risk social science research. We informed the respondents about the study's purpose and obtained their consent to participate by having them complete the questionnaire. We did not include minors or vulnerable populations, nor did we apply any experimental interventions. We aligned the research design with ethical research conduct principles, which include respect for privacy, informed consent, and confidentiality.

UNDER PEER REVIEW

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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UNDER PEER REVIEW