

Exploring the Impact of Social Media Usage Patterns on General Engagement: A Behavioural Analysis of Transgender Persons Residing in Selected Districts of Bihar, India

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Abstract

Social media is one of the main networks for transgender people to find spaces for expression, activism, and community. The platforms, such as Instagram, Twitter, and TikTok, amplify transgender voices, raising awareness and advocacy. Social media is also a minefield of cyberbullies, misinformation, and discrimination. Even with its shortcomings, when deployed responsibly, it can do much to empower transgender individuals by encouraging visibility, acceptance, and chances to interact socially and professionally. In this study, an attempt has been made to understand the behavioural pattern of social media usage by transgender persons residing in selected districts of Bihar, namely Patna, Ara, Muzaffarpur, Bhagalpur, and Purnea. To execute this study, a questionnaire, namely 'The Social Media Use Scale: Development and Validation,' has been used, under which there are four different scales, namely Image-Based Social Media Use, Comparison-Based Social Media Use, Belief-Based Social Media Use, and Consumption-Based Social Media Use. 330 responses have been taken into consideration. For analysis of the data, firstly, exploratory factor analysis has been done, followed by multiple linear regression analysis. The purpose of this study is to analyse the impact of different scales on the general social media usage by transgender persons. The results clarify that all the scales positively impact the general social media usage pattern of transgender people, with Consumption-Based Social Media Use having the greatest effect, followed by Comparison-Based Social Media Use. Belief-Based Social Media Use and Image-Based Social Media Use have smaller yet significant roles.

Keywords: social media, transgender persons, behavioural pattern, usage

1. Introduction

Social media has evolved into a cornerstone of daily existence, providing channels for connection, expression, and information dissemination. For transgender people, such platforms provide key environments for working through and asserting identities, finding supportive communities, and doing advocacy. Transgender and gender-diverse (TGD) adolescents frequently experience the heightened incidence of mental health problems (e.g., anxiety, depression, body dysmorphia) associated with their gender identity, and studies show they turn to social media for positive reinforcement and community (Herrmann Lena et al., 2024). One of social media's most significant advantages for transgender individuals is the ability to undergo and express identity management across a variety of sites. Research on managing gender identity on internet discussions found that the extent to which one share about their identity affected how one has interacted and which content are shared, showing the complexity with which transgender people negotiate their online presence to balance authenticity with safety (Buss Justin et al., 2021). Additionally, social media allows for the formation of communities where transgender people can compare notes, seek advice, and support one another. These spaces not only alleviate the stress of feeling alone, but also provide a sense of community and belonging, which is important for mental well-being. Hence, as this dichotomous aspect reminds, it requires coping measures to overcome, avoid or minimizing adverse interactions while maximizing positive experiences (Aldridge Zoe et al., 2024). It is these wider social aspects that have changed through the introduction of social media in the digital age and how we express our identities, share our talents and communicate with broader communities.

(Budge Stephanie L. et al., 2012) has expressed the coping mechanisms and emotional challenges that are continuously faced by transgender individuals and hence emphasized on the idea of representation's importance. These people suffer a lot of workplace discrimination and there is a need for inclusive efforts to make them efficient in all walks of life (Tetreault Patricia A et al., 2013). Similarly, (Galupo M. Paz et al., 2014) has examined the microaggressions and their subsequent effects on transgender people as social media has allowed transgender persons, who for years have been marginalized, discriminated against, and made practically invisible in mainstream media and traditional industries. (McFadden Ciaran & Henry Marian Crowley, 2017) have highlighted how representation of transgender people as a normal human being improves their inclusivity and mitigates their marginalization. Social media has provided them a stage to express themselves, display their skills and advocate for themselves which were missing from a very long time. Rather, in the sense, that social media is democratic; it breaks down barriers and gives those invisible voices room to make noise and be seen. Social platforms from Instagram to YouTube, TikTok and LinkedIn have introduced the world to transgender talent with accounts that open a window into a diverse life experience while offering thought-starters for workplace inclusivity, diversity and equality. (Brannon Tiffany N. & Lin Andy, 2021) have emphasized on the impact of social media campaigns like #HireTrans and corporate efforts for their inclusivity in mainstream society. With social media, transgender people can skip the gatekeepers of employers and media executives and tell their own stories. Through sharing their creation trans creators can circumvent the traditional industries through which we learn about art, music, fashion, performance and entrepreneurship to demonstrate their abilities directly to an audience both global in access and scale. It has enabled many transgender people to launch careers as influencers, artists and advocates — and helped them get noticed for their talents and creative work in ways that were impractical if not impossible. For this reason, and for inspirational figures like Chella Man (a transgender and deaf artist, model and activist), who have used social media to share his art, fashion sense and advocacy — ultimately gaining thousands of followers on platforms such as Instagram or YouTube as well to demonstrate that these tools can indeed be used in powerful ways that both humans can use to empower themselves personally as well professionally (Man Chella, 2020). Activism is another important facet of how transgender people are using social media. Digital platforms serve an advocacy role, in which transgender people — as well as allies — can mobilize support for policies, push back against discriminatory laws and raise awareness about violence against the trans community. Campaigns like Transgender Day of Visibility and Trans Awareness Week are powerful because they are lifted by social media, which enables trans people to take ownership of their narratives and advocate for shifts in society. Additionally, crowdfunding using websites such as 'GoFundMe' has become a key source of support for many transgender people in search of gender-affirming health care, legal fees or financial support.

But social media is not without its challenges. Transgender people are often subjects of cyberbullying, harassment and misinformation online. These obstacles notwithstanding, many still use the digital realm for advocacy, self-acceptance, and community-building. As social media continues to develop, it is a fundamental force for transgender people to go through their lives, share their experiences, and push for equality in a world that is becoming even more globalized.

2. Background

Social media platforms also have become ubiquitous in the lives of transgender individuals, providing sites for exploration of their identity, shared community and avenues to advocate. It plays a key role in how transgender individuals explore and affirm their gender identities. LBT Women, for instance, often come to be queer and diverse through social media and find a different realm to identify themselves and seek language and framework that befits their journey in life (Hammack Philip L. & Manago Adriana M., 2024). This process is especially important for those without offline support networks, since online communities bring validation and a sense of connection. Control of self-presentation and connecting with those also doing so creates a safe space for identity development. Through online community formation, it provides trans individuals with access to social support communities which may not be viable in the individual's environment. Trans adolescents report using social media to connect with peers for support, share their experiences and find information relevant to their gender identity (Selkie Ellen et al., 2020). These virtual communities can help reduce isolation and provide emotional support that is especially important given the higher mental health risks for transgender populations. But support differs in quality, and negative online engagement has the power to amplify mental health problems. Content creators and influencers like Alok Vaid-Menon, Nikita Dragun and Chella Man use their platforms to speak out against transphobia, celebrate nonbinary people and share their personal journeys towards self-discovery. Through videos, blogs and live sessions, they have ignited global conversations, breaking dated conventions and calling for allyship. Research shows that the consumption of transgender narratives on social media has the potential to enhance audiences empathetic standing and minimize prejudice towards transgender individuals (Miller Ryan A. et al., 2020).

Hence, Social media acts as both a pro and con in the lives of transgender people. The role is nuanced, with both positive and negative aspects affecting well-being among transgender users. Future studies should further investigate these dynamics and inform strategies to maximize the supportive dimensions of social media while minimizing its

challenges. For effective interventions and policies promoting inclusivity and mental health, it is crucial to comprehend how social media usage affects the experiences of transgender people.

3. Method

3.1 Questionnaire Formation

In order to study the social media usage by transgender people, the questionnaire developed by (Tuck Alison B. & Thompson Renee J., 2023) has been taken. The questionnaire contains three sections. The first section comprises of the demographic information like age, gender, income etc. The second section comprises of general social media usage by the respondents on average per day. The third section comprises of social media use scale by the respondents. For mentioning their engagement on social media in the past week, the scale was mentioned as follows:

1=Never, 2=1-2 times per week, 3=3-4 times per week, 4=5-6 times per week, 5= once daily, 6=2-5 times daily, 7=6-9 times daily, 8= 10-13 times daily, 9=Hourly or more.

Under this section, the four constructs are given namely, Image -Based Social Media Use, Comparison-Based Social Media Use, Belief-Based Social Media Use and Consumption-Based Social Media Use. Under each construct, certain indicators are given.

3.2 Data Collection

The data were collected via snowball sampling technique because it is not that easy to contact transgender people and be directly in touch with them. To have one-on-one discussion with stigmatized population like transgender people, it is viable only when they are contacted easily. Hence, the snowball sampling technique which is a non-probability sampling worked wonders in this case. The process of data collection started from some known residential areas of Patna district where transgender community mostly reside. That one start of the loop helped to reach different transgender people who reside in other areas of Patna. Likewise, they were contacted steadily and the loop continued to move on, giving the respondents from the districts like Patna, Ara, Bhagalpur, Muzaffarpur and Purnea. For this, questionnaires were distributed among them in both online and offline mode, as per their consideration. Some stipulated time was given to them to fill the questionnaires as has been asked by them. Approx 400 questionnaires were distributed in totality. The total number of properly filled-in questionnaires obtained was 330 in number. All the samples collected were purely based on non-probability sampling. The sample collected during this procedure was proved appropriate for the study and hence it was executed successfully.

3.3 Data Analysis Technique

As mentioned above, the questionnaire has three sections. The third section contains different constructs under which there are relevant questions. In order to perform the analysis, initially Exploratory Factor Analysis was done. It identifies latent factors by providing grouping of correlated variables acting together and helps to reduce the complexity of data. When conducting factor analysis, the goal is to identify the factor structure of a data set, to evaluate dimensionality, and to improve measurement scales. In particular, EFA helps to identify latent constructs, from which the extent to which survey or test items represent the theoretical constructs they are intended to assess can be determined. Hence, performing EFA initially proved to be beneficial here. Later on, Multiple Linear Regression Analysis was performed in order to understand the impact of different variables on general social media usage. This analysis helped to delve into the behavioral pattern of general social media usage by transgender people and the way it affects their well-being in day-to-day life.

For running both the analysis, namely, Exploratory Factor Analysis and Multiple Linear Regression Analysis, IBM SPSS (Statistical Package for Social Sciences) ver. 26 was used and the subsequent result was found out.

Demographic Variables Used

The following variables were extracted from the questionnaire:

- Age
- Religion
- Birth Gender
- Gender Role that describes them
- Income
- Regions

Apart from that, the questionnaire gave the following variables: -

Dependent Variable

- General Social Media Usage

Independent Variables

- Image-Based Social Media Use
- Comparison-Based Social Media Use
- Belief-Based Social Media Use
- Consumption-Based Social Media Use

3.4 Hypothesis

On the basis of nature of the study and the questionnaire taken, following hypotheses have been framed:

- H1: Image-Based Social Media Use has a significant positive impact on General Social Media Usage by transgender persons.
- H2: Comparison-Based Social Media Use has a significant positive impact on General Social Media Usage by transgender persons.
- H3: Belief-Based Social Media Use has a significant positive impact on General Social Media Usage by transgender persons.
- H4: Consumption-Based Social Media Use has a significant positive impact on General Social Media Usage by transgender persons.

3.5 The Model

In this study, the model has been framed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon \quad (1)$$

Where Y represents General Social Media Usage by transgender persons. β_0 is the intercept value. X_1 to X_4 are the four independent variables namely, Image based social media use, comparison based social media use, belief-based social media use and consumption-based social media use. β_1 to β_4 are the estimated regression coefficients of independent variables used here. ϵ is the model error, i.e., the variation of our estimate of Y with respect to the real value.

4. Results

The results obtained from different sections of the questionnaire are demarcated as follows:

4.1 Section A: Demographic Profile

The data collected from 330 respondents from different selected districts of Bihar was arranged systematically. The following section contains demographic profile of the respondents: -

Table 1. Demographic Profile of the Respondents

Demographics	Categories	Frequency	Percent
Age (Years)	15-24	48	14.54
	25-34	90	27.27
	35-44	87	26.36
	45-54	86	26.06
	55 years or older	19	05.77
Religion	Hindu	287	86.96
	Muslim	43	13.04
Birth Gender	Male	138	41.81
	Female	160	48.48
	Intersex	32	09.71
Gender role that describes you	Female to Male	120	36.36
	Male to Female	86	26.06
	Genderqueer	52	15.75
	Binary	23	06.96
	Intersex	19	05.75
Income	Gender non-conformity	30	09.12
	0-25000	286	86.66
	25000-50000	34	10.30
	50000-75000	08	02.42
Regions	75000 and above	02	0.62
	Patna	176	53.33
	Ara	36	10.90
	Bhagalpur	38	11.51
	Muzaffarpur	42	12.72
	Purnea	38	11.54

80% of the respondents are in the 25-54 age group so this study mostly includes working age adults, with a minimal representation of 15-24 or 55+ age groups. Almost 87 percent of the participants are Hindu, and only 13 percent are Muslim. A majority of respondents were born female (48.48%), while some respondents were born male (41.81%), and a similar sized cohort (over 10%) identified as intersex. Most of the respondents are Female to Male (36.36%) followed by Male to Female (26.06%). Gender other identities such as Genderqueer (15.75%) and Gender Non-Conforming (9.12%) are also well represented. The great majority (86.66%) make ₹25000 or lesser which show they belong to lower income category. Only 3% of the respondents claim to earn above ₹50,000. 53.33% of the total respondents hailed from Patna, with Muzaffarpur, Bhagalpur, Purnea, and Ara having a relatively equal representation among the rest.

4.2 Section B: General Social Media Usage

In the second section of the questionnaire, the question was related to general social media usage. The question was as follows: 'On average, how many hours per day do you spend on social networking sites (e.g., Instagram, Facebook, etc.)'.

To make the answers convenient, the options was converted into Likert Scale as follows:

1 hour, 2 hours, 3 hours, 4 hours, 5 hours and 6 hours.

The data obtained from the respondents are tabulated as follows:

Table 2. Time Spent on Social Networking Sites Per Day

Average Number of Hours per Day spent on Social Networking Sites	Frequency	Percentage
1	36	10.9
2	18	5.5
3	129	39.1
4	56	17.0
5	53	16.1
6	38	11.5
Total	330	100

Interpretation of the Table:

1. The total number of respondents surveyed is 330, representing 100% of the sample.
2. Most Common Usage (Mode): The majority belong to the category which spend 3 hours/day on social networking sites (129 respondents, 39.1%). It means 3 hours spent online is the most frequent.
3. Low Usage (1-2 Hours): 36 respondents (10.9%) spend 1 hour every day. 18 respondents (5.5%) are spending 2 hours a day. These categories encompass 16.4% of the sample, suggesting an even smaller share of light social media users that falls into this category.
4. Moderate Usage (4-5 Hours): 4 hours daily of 56 respondents (17.0%). The 53 responders (16.1%) spend 5 hours a day. This category constituted 33.1% of the sample, this shows that a major portion of users used to spend hours on social media every day.
5. High Usage (6 Hours and Over): 38(11.5%) spend for 6 hours in a day. This represents a significant minority who are heavy users of the platforms.

Implication:

This number collectively represents diversity in social media engagement which means most of the respondents are spending around 3 to 5 hours per day on social media. This might indicate extensive use of digital technology, which can have an impact on social habits, productivity, and mental health.

4.3 Section 3: Social Media Use Scale

In this section, four scales namely Image-Based Social Media Use, Comparison-Based Social Media Use, Belief-Based Social Media Use and Consumption-Based Social Media Use are considered. Under each scale there are certain questions that attributes them. The question related to this scale is as follows: 'Please indicate how frequently you have engaged in each of the following social media activities in the past week (7 days). Use the following scale: 1=Never, 2= 1-2 times per week, 3=3-4 times per week, 4= 5-6 times per week, 5=Once daily, 6= 2-5 times daily 7= 6-9 times daily, 8=10-13 times daily, 9=Hourly or more'

The indicators under each construct are given as follows:

Image-Based Social Media Use	Comparison-Based Social Media Use	Belief-Based Social Media Use	Consumption-Based Social Media Use
Made/shared a post or story about something positive that was personally about me.	Compared my body or appearance to others'	Made/shared a post or story about something negative that was personally about me.	Scrolled aimlessly through my feed(s)
Looked at how many people liked, commented on, shared my content or followed/friended me.	Compared my life or experience to others'	Made/shared a post or story about something negative that was NOT personally about me.	Looked at others' stories.
Read comments to my own content.	Reminisced about the past.	Commented unsupportively or disliked/ "reacted" unsupportively on others' post(s).	Navigated to others' profiles in my social network (e.g., friends or friends of friends)
Edited and/or deleted my own social content.		Sought out content that I morally or ethically disagreed with.	Navigated to others' pages who I do not know (e.g., influencers or other famous people)
Played with photo filtering/photo editing			Watched videos such as memes, news content, how-to/recipes, etc.

In order to study the impact of different Social Media Use Scale on General Social Media Usage by the respondents, the analysis was started sequentially as mentioned below: -

4.4 Exploratory Factor Analysis

4.4.1 Sampling Adequacy

When performing factor analysis, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (Kaiser Henry F., 1960) and Bartlett's Test of Sphericity (Tobias Sigmund & Carlson James E., 2010) are used to determine whether a dataset is ready for factor extraction. These tests are done to check whether there is correlation between the variables in the dataset and whether factor analysis can be performed.

(a) KMO and Bartlett's Test of Sphericity

Table 3. Table for Sampling Adequacy

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.866
Bartlett's Test of Sphericity	Approx. Chi-Square	4743.536
	df	136
	Sig.	.000

Normally, KMO test is used to measure the suitability of the dataset for factor analysis based on the proportion of variance in the variables, which can be explained by the underlying factor. It essentially tests the degree of linear intercorrelations between the variables and whether their arrangement is appropriate to structure detection by factor analysis. Our KMO is 0.866, in the "great" range (≥ 0.80). This implies that the variance in the dataset is general across variables rather than unique to a variable. Factor analysis is well suited for this dataset. Both procedures show a good sampling adequacy which confirm the variables to be considered for forming the underlying factors.

Bartlett's Test of Sphericity

This test checks the correlation matrix of the dataset with an identity matrix. A correlation matrix that is an identity matrix (the variables are completely uncorrelated) is a bad condition for factor analysis. A high Bartlett's test ($p < 0.05$) indicates that the variables are correlated enough to perform factor analysis. Here, Chi square = 4743.536. This is also a relatively high chi square indicating strong association. Degrees of Freedom (df) = 136. Degrees of freedom vary in relation to the number of variables present in the dataset and their relationships. The value of Significance (Sig.) is 0.000. A p-value (Sig.) ($p < 0.05$) with a null hypothesis of a 0.000 is a non-identity correlation matrix. Such results suggest that factor analysis is appropriate because the dataset has relationships between variables that make sense. Hence, KMO = 0.866 (great). This shows good common variance in the dataset.

The KMO and Bartlett's Test results show that the data was very fit for EFA. The high KMO value (0.866) indicates that the sampling adequacy is adequate and Bartlett's test is significant ($p < 0.05$), which implies that correlation among variables is suitable for factor extraction. Thus, factor analysis may continue to uncover the underlying latent constructs.

4.4.2 Reliability Test for Each Component

Reliability test is performed using Cronbach's Alpha method to measure internal consistency for each component (Cronbach Lee J., 1951). Cronbach's Alpha Outcomes range from 0 to 1 and the closer to 1, the better the internal consistency is. In social science research, a test can be considered reliable if the value is around 0.7.

Table 4. Reliability Test

Components	Total No. of Respondents	No. of Items	Cronbach's Alpha
Image based Social Media Use	330	05	0.886
Comparison based Social Media Use	330	03	0.898
Belief based Social Media Use	330	04	0.926
Consumption based Social Media Use	330	05	0.937

The five items measuring Image-Based Social Media Use received the Cronbach's Alpha value of 0.886, evidencing excellent reliability. This indicates that the items are very consistent in measuring this construct. For three items measuring Comparison-Based Social Media Use, the Cronbach's Alpha (α) value is 0.898, indicating excellent reliability. This means that the items are aligned well and the construct is measured consistently. The 0.926 value of Cronbach's Alpha proves excellent reliability of four items measuring the Belief-Based Social Media Use. The high consistency indicates the high coherence between the items in this construct. Cronbach's Alpha coefficient for the five items measuring Consumption-Based Social Media Use was 0.937, thus indicating excellent reliability. These items have a strong fit, and reliably measure the latent construct. Cronbach's Alpha of all four components (greater than 0.85) indicates good internal consistency and reliability of the scales. The internal consistency of the items in each component ensures that they are measuring the same construct within each component and can therefore be confidently used in subsequent analyses.

4.4.3 Communalities

The extracted values of communalities of each variable are represented as follows:

Table 5. Communalities

Variables	Initial	Extraction	Interpretation
IB1	1.000	.794	Well represented
IB2	1.000	.623	Moderately represented
IB3	1.000	.577	Moderately represented
IB4	1.000	.689	Well represented
IB5	1.000	.797	Well represented
CM1	1.000	.788	Well represented
CM2	1.000	.853	Strongly represented
CM3	1.000	.875	Strongly represented
BB1	1.000	.718	Well represented
BB2	1.000	.810	Strongly represented
BB3	1.000	.863	Strongly represented
BB4	1.000	.901	Strongly represented
CN1	1.000	.867	Strongly represented
CN2	1.000	.664	Well represented
CN3	1.000	.782	Well represented
CN4	1.000	.819	Strongly represented
CN5	1.000	.882	Strongly represented

Extraction Method: Principal Component Analysis.

The Table 5 shows that all variables have high communalities (above 0.5), demonstrating that they are meaningfully represented by the extracted factors. The variables CM2 (0.853), CM3 (0.875), BB4 (0.901), CN5 (0.882), and CN1 (0.867) show the highest communalities which indicates that they are best explained by the extracted factors. IB3 (0.577) and IB2 (0.623) have the lowest communalities, but that is still in the acceptable range. This suggests that variance in the variables is well-defined by the factor model, confirming support of the validity of factors being extracted in the EFA process.

4.4.4 Total Variance Extracted

The following table represents the total variance explained in the taken components:

Table 6. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.076	41.622	41.622	7.076	41.622	41.622	4.058	23.870	23.870
2	2.716	15.976	57.598	2.716	15.976	57.598	3.535	20.793	44.663
3	2.415	14.205	71.803	2.415	14.205	71.803	3.335	19.616	64.279
4	1.098	6.460	78.263	1.098	6.460	78.263	2.377	13.984	78.263
5	.625	3.679	81.943						
6	.490	2.881	84.824						
7	.458	2.693	87.517						
8	.404	2.376	89.893						
9	.357	2.102	91.995						
10	.255	1.502	93.497						
11	.241	1.418	94.915						
12	.206	1.212	96.127						
13	.177	1.040	97.167						
14	.171	1.006	98.173						
15	.125	.737	98.910						
16	.111	.651	99.561						
17	.075	.439	100.000						

Extraction Method: Principal Component Analysis.

Four factors were extracted, based on eigenvalues exceeding 1.0 (Kaiser Henry F., 1960). Beyond Factor 4 (eigenvalue = 1.098, 6.46% variance), the eigenvalues are less than 1, indicating no additional factors provide value. These four variables account for 78.26% of the total variance in the data, reflecting high degree of interaction among them. Factor 1 accounted for 41.62% of the total variance before rotation, but this variance was spread more evenly across four factors (23.87%, 20.79%, 19.62%, and 13.98%) after rotation. This means that the interpretable meaning of the Factor decomposition is improved by enabling mutual orthogonality, which avoids a single factor from dominating the explanation. Components 5 to 17 have eigenvalues less than 1 which means they do not explain enough variance and were not retained in the final model. This rotation balanced factor contributions so that interpretation was simpler. Because these four factors most likely refer to the four kinds of social media use behaviours i.e., Image-Based, Comparison-Based, Belief-Based, and Consumption-Based Social Media Use. These results of the EFA collectively validate the fact that the data set is appropriate for the factor analysis with four significant constructs representing social media usage trends.

4.4.5 Scree Plot

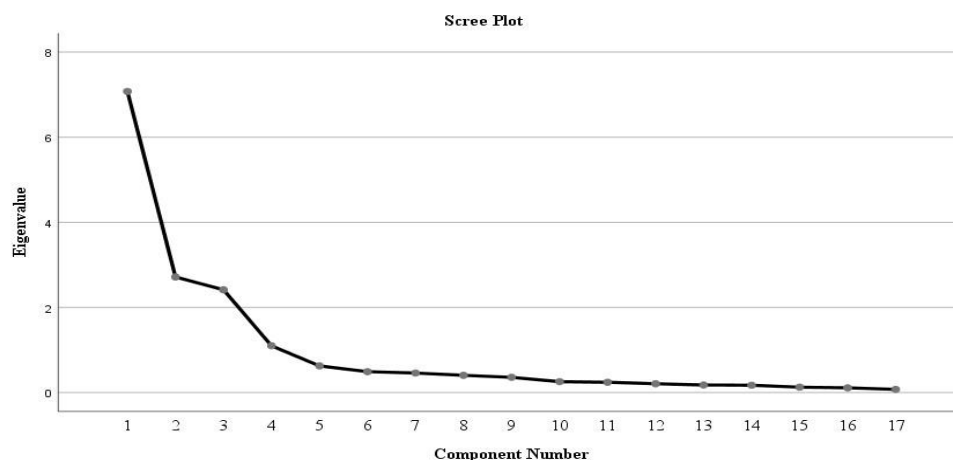


Figure 1. Scree Plot

An EFA Scree Plot has been used to identify optimal number of factors to retain. Here, components 1 to 4 have eigenvalues much larger than 1 meaning that they explain a lot of variances. After Component 4, the eigenvalues take a steep decline and then level out, creating a straight line or “scree.” The elbow appears at Component 4, indicating 4 factors should be retained for analysis. Therefore, according to the scree plot it was decided that 4 factors should be

kept as these have been responsible for the majority of variance. Furthermore, component beyond the 4th factor explained little variance and makes no sense in the context of the analysis. This result is consistent with our Total Variance Explained table seen in the previous interpretation, supporting the conclusion that 4 factors are optimal for the dataset.

4.4.6 Rotated Component Matrix

The Factor loadings for each variable on the extracted components after rotation (Varimax with Kaiser Normalization) are provided in the Rotated Component Matrix. The absolute loading is higher when the absolute value is higher, which indicates that the variable greatly contributes to the particular component. Anything greater than a loading of 0.5 is usually considered significant. Then, each variable is assigned to the factor where it has the highest loading. In this case the Varimax rotation is applied that maximizes the variance of factor loadings over variables, allowing the variables to align with some factors and in turn making interpretation easier.

Table 7. Rotated Component Matrix

Variable	Component 1	Component 2	Component 3	Component 4	Assigned Factor
IB1	0.170	0.852	0.032	0.195	Factor 2 (Image-Based)
IB2	0.142	0.720	0.139	0.256	Factor 2 (Image-Based)
IB3	0.138	0.700	0.194	0.175	Factor 2 (Image-Based)
IB4	0.211	0.771	0.018	0.222	Factor 2 (Image-Based)
IB5	0.264	0.830	0.073	0.181	Factor 2 (Image-Based)
CM1	0.235	0.367	0.122	0.764	Factor 4 (Comparison-Based)
CM2	0.111	0.303	0.144	0.853	Factor 4 (Comparison-Based)
CM3	0.081	0.289	0.193	0.865	Factor 4 (Comparison-Based)
BB1	0.028	0.155	0.828	0.092	Factor 3 (Belief-Based)
BB2	0.163	0.081	0.867	0.159	Factor 3 (Belief-Based)
BB3	0.166	0.067	0.908	0.078	Factor 3 (Belief-Based)
BB4	0.087	0.072	0.936	0.113	Factor 3 (Belief-Based)
CN1	0.906	0.182	0.081	0.080	Factor 1 (Consumption-Based)
CN2	0.753	0.221	0.176	0.131	Factor 1 (Consumption-Based)
CN3	0.857	0.170	0.094	0.096	Factor 1 (Consumption-Based)
CN4	0.881	0.161	0.087	0.096	Factor 1 (Consumption-Based)
CN5	0.916	0.172	0.081	0.085	Factor 1 (Consumption-Based)

The rotated component matrix identifies four unique factors for the variables based on loadings. The behavioural patterns of social media use are hypothesized to align closely with each factor, confirming the validity of the factors that have been extracted. Accordingly, these constructs and the indicators have been used to study the effect on General Social Media Usage by transgender persons. The result of the multiple linear regression analysis has been recorded and summarized as follows.

4.5 Regression Analysis

Regression Analysis is the process of examining the relationship between dependent and independent variables, where the dependent variable is being tested to see if it can be predicted by the independent variables that will be carrying a value. It assists in making predictions, recognising trends, and making data-backed decisions. In addition, to helping identify relationships, regression helps in better understand the strength and significance of those relationships and measure the influence of certain factors on key outcomes.

In our study, the following model summary after executing regression analysis has been achieved:

Table 8. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.837 ^a	.701	.697	.783

a. Predictors: (Constant), Consumption Based Social Media use, Belief Based Social Media use, Comparison Based Social Media use, Image Based Social Media use

Interpretation of the Model:

The Multiple Correlation Coefficient (R) is 0.837 which indicates strong positive correlation of the predictors (Consumption-Based, Belief-Based, Comparison-Based and Image-Based Social Media Use) in this model with the dependent variable (General Social Media Usage/ Usage). R Squared (Coefficient of Determination) = 0.701, 70.1% variance in dependent variable is explained by independent variables included in model. This indicates a very good model for prediction of dependent variable. Hence, from the value the Adjusted R Square is 0.697 which mean 69.7%

of variance is explained. The average distance of observed values falls from the regression line — Standard Error of the Estimate is 0.783. A standard error of 0.783 here indicates a good fit. Thus, the regression analysis indicates that the independent variables have a significant joint effect on the dependent variable. It can thus be considered as a robust and valid predictive model of the studied phenomenon with some 70 percent of variance explained.

4.5.1 ANOVA

An ANOVA (analysis of variance) table is used to check if the means of variety of groups are statistically significantly different. It helps in comparing variations within and between groups to assess the impact of independent variables on a dependent variable, ensuring reliable conclusions in experimental and observational studies.

Table 9. ANOVA Table

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	467.685	4	116.921	190.494	.000 ^b
Residual	199.479	325	.614		
Total	667.164	329			

a. Dependent Variable: General Social Media Usage

b. Predictors: (Constant), Consumption Based Social Media use, Belief Based Social Media use, Comparison Based Social Media use, Image Based Social Media use

(Analysis of Variance) table testing whether the model (independent variables) significantly explains a proportion of the variance in the dependent variable. The p-value Sig. * (*p < 0.000) is highly significant as it suggests the Independent Variables collectively (Consumption Based + Belief Based + Comparison Based + Image Based) have an impact on the dependent variable when analysing General Social Media Usage. Now, the F-statistic (190.494) is quite high, which strengthens the conclusion that the independent variables explain a lot more variability than expected under the null hypothesis. The ratio SSR = 467.685 and SSE = 199.479 indicate that the predictors accounts for a large proportion of the variation, the remaining unexplained variance indicates high explanatory power.

The ANOVA output validates the model for further interpretability and practical applications.

4.5.2 Final Regression Model

The following table represents the final regression model of this study:

Table 10. Final Regression Model: Impact on General Social Media Usage

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-.444	.158		-2.816	.005		
Image Based Social Media use	.145	.033	.175	4.345	.000	.568	1.761
Comparison Based Social Media use	.259	.030	.341	8.693	.000	.598	1.671
Belief Based Social Media use	.102	.024	.137	4.201	.000	.863	1.159
Consumption Based Social Media use	.316	.024	.457	13.261	.000	.775	1.291

a. Dependent Variable: General Social Media Usage

Here, there is no multicollinearity as tolerance is more than 0.1 whereas VIF is less than 10 in the case of all the four predictors meaning that multicollinearity does not affect the overall stability of the model.

This regression analysis assesses the impact of predictors on the dependent variable. The results are summarized as below:

Table 11. Hypothesis Testing Table

Null Hypothesis	Unstandardized Coefficient (B)	Standardized Coefficient (Beta)	p-value (Sig.)	Reject/Accept Null Hypothesis	Conclusion
1) H0: Image-Based Social Media Use has no significant impact on General Social Media Usage.	0.145	0.175	0.000	Null Hypothesis Rejected	Image-Based Social Media Use has a significant positive impact on General Social Media Usage.
2) H0: Comparison-Based Social Media Use has no significant impact on General Social Media Usage.	0.259	0.341	0.000	Null Hypothesis Rejected	Comparison-Based Social Media Use has a significant positive impact on General Social Media Usage.
3) H0: Belief-Based Social Media Use has no significant impact on General Social Media Usage.	0.102	0.137	0.000	Null Hypothesis Rejected	Belief-Based Social Media Use has a significant positive impact on General Social Media Usage.
4) H0: Consumption-Based Social Media Use has no significant impact on General Social Media Usage.	0.316	0.457	0.000	Null Hypothesis Rejected	Consumption-Based Social Media Use has a significant positive impact on General Social Media Usage.

Impact Studies and Interpretation:

❖ Image-Based Social Media Use:

Unstandardized Coefficient(B): 0.145, meaning that for one unit of Image-Based Social Media Use increases the General Social Media Usage by 0.145 unit. Beta = 0.175 [positive correlation)] So, Image Based Social Media Use is a substantial predictor of General Social Media Usage.

❖ Comparison-Based Social Media Use:

Unstandardized Coefficient (B): 0.259, meaning that for one-unit increase of Comparison Based Social Media Use leads to a 0.259 unit increase in General Social Media Usage. The Beta value (0.341) shows a significant positive effect. Therefore, Comparison-Based Social Media Use is a key predictor of General Social Media Usage.

❖ Belief-Based Social Media Use:

Unstandardized Coefficient (B): 0.102, meaning that for every unit increase in Belief-Based Social Media Use, one can expect a 0.102 unit increase in General Social Media Usage. Beta value (0.137) shows a moderate positive impact. Thus, Belief-Based Social Media Use is a significant predictor but with less relative impact than the other predictors.

❖ Consumption-Based Social Media Usage:

Unstandardized Coefficient (B): 0.316 means there is a 0.316 unit increase in General Social Media Usage when one unit increases of Consumption-Based Social Media Use. Beta (0.457) recorded the highest positive effect among all variables. Therefore, Consumption-Based Social Media Use is the strongest predictor of General Social Media Usage. Therefore, from the model, it can be inferred that all four independent variables are significantly positively correlated with General Social Media Usage ($p < 0.05$ each). Consumption-Based Social Media Use (Beta = 0.457) has the greatest effect, followed by Comparison-Based Social Media Use (Beta = 0.341). Belief-Based Social Media Use (Beta = 0.137), and Image-Based Social Media Use (Beta = 0.175) have smaller yet significant roles. Results indicate one important feature of the transgender people—adults above certain age groups benefit much more than significantly lesser in a specific way due to their usage of social media, but with its cost, as past studies have found (Craig Shelley L. et al., 2015, 2021). (Buss Justin et al., 2021) apart from that has mentioned in his study that transgender people are carving the niche in the identity management as it has given them a new hope and purpose of living without judgements. Likewise, (Selkie Ellen et al., 2020) has described the role of social media in social support for transgender persons which also indicates a major significance of consumption-based usage. One important research by (Aldridge Zoe et al., 2024) has highlighted the things that the online community constructed by the transgender people on social media are really helpful for their overall well-being but at the same time the online community sometimes lead them to the unintentional exposure of transphobia which can be fatal if not controlled properly. This is a great mirror of comparative use of social media. Therefore, it can be said in short that social media is a glass of water that only differs in perspective based on the intention of usage.

5. Conclusion

Although the motivations for using social media differ from person to person, several trends can be observed when viewing usage through different perspectives. The hierarchy of motivations behind social media engagement is apparent, ranking from consumption-based use, comparison-based use, image-based use, to belief-based use. This top-down approach indicates that social media is most commonly used by transgender persons for content consumption at first, but as interactions deepen, social and self-image considerations influence those interactions, which are then followed by belief systems in the bottom half of the above ranking. In contrast to producing, consumption-based social media use focuses on users who are passively consuming content, watching or scrolling through it but not producing or contributing to it. This shows that majority of all social media users like this type of audience which sees content just for the sake of entertainment or information or leisure. Social media is a wonderful tool content consumption for endless scrolling, algorithmic tailored content, and a range of media formats. The platforms including YouTube, TikTok, Instagram and Twitter exploit this inclination through endless feeds, autoplay and customized suggestions. Social media on one hand inspires people to aim higher, be better, and aspire. Alternatively, too much comparison may result in damaging self-views, anxiety, and lower self-dignity, particularly when they compare their realities each with highly curated hyperbolic depictions of others. Studies have found that those who do a lot of comparison-based use are at a higher risk for feelings of inadequacy, dissatisfaction and mental health issues. Platforms such as Twitter, Facebook, and Reddit serve at the heart of online belief-based discussions, where users discuss everything from politics and social justice to religion and ethics. Ideas can go viral and users can draw attention, rally support for movements and contest dominant narratives. Examples of how social media can be used for real-world change include hashtag activism, with campaigns like #BlackLivesMatter, #MeToo, and #TransRightsAreHumanRights. But belief-based use has risks as well, including echo chambers, misinformation, and online polarization. Algorithms typically strengthen users' existing beliefs by exposing them to content that confirms their views, creating ideological bubbles in which they are less exposed to ideas that contradict their own. Moreover, misinformation and propaganda have become so pervasive that users often struggle to tell credible sources from bought narratives. However, these challenges do not discount belief-based use as a critical part of social media, encouraging discourse and joint effort over significant social matters.

6. Policy Implications

For transgender individuals, social media is an essential tool for self-expression, community support, and advocacy. But public policies governing social media can affect their safety, privacy and access to affirming spaces directly. Public policy in this regard has significant consequences in terms of free speech and expression of identity. Transgender people can use social media to experiment or express their gender identity in ways unavailable in offline spaces. Policies restricting content about gender identity — whether through censorship, mis-categorization of transgender-related conversations as “sensitive” content or shadow banning — can hinder their ability to connect with supportive communities and share their experiences. This can heighten feelings of loneliness and worsen mental health problems, such as anxiety and depression. Privacy and data protection is another major issue. Many transgender people face discrimination or violence when their identity is revealed without their consent. Policies requiring real-name use, excessive confirmation of identity or government oversight of social-media accounts can expose transgender users to the risk of being outed. This is all the more alarming in the parts of the world where transgender rights lack legal standards, which could also put individuals at risk of job loss, harassment, or jail time. In turn, stronger data protection policies that safeguard personal information are the key to ensure their safety. Finally, public policy shapes the public response to misinformation and hate speech related to transgender people. Social media platforms are often battlegrounds for misinformation activities, creating and amplifying stigma and discrimination. And policies that take no affirmative steps to combat hate speech — or hold tracking users accountable for causing more targeted and organized harassment — enable what can be a hostile online ecosystem. On the other hand, good policies like enforcing anti-harassment measures and encouraging digital inclusiveness can lead to a safer place for transgender people to interact without fear of being targeted. In addition, public policy decisions can impact access to essential resources. Social media is an important source of information about healthcare, legal rights and social support networks for many transgender people. Bans on talking about certain specific topics — especially those related to gender-affirming care — can hinder them from accessing necessary information about their options, which could jeopardize their health and safety. Ultimately, social media usage policies play a crucial role in shaping the rights, safety, and access of transgender individuals to supportive communities. Policymakers need to carefully weigh these implications and strive for regulatory frameworks that promote inclusivity, privacy and protection against discrimination.

7. Limitations

The main limitations of this study have been described as follows:

Snowball sampling is a popular form of non-probability sampling, especially in studies of hidden, hard to reach, or

stigmatized populations. It starts with seeds — a small group of initial study participants — recruiting others from their social networks. This loop goes on, as it is a chain like process and the sample size is increased via referral. It is particularly useful for working with marginalized communities or in studying illicit behaviour or rare medical conditions, as researchers may not have direct access to participants, as is common in typical studies. Nonetheless, there are important limitations with this approach regarding self-reporting and geographical representativeness.

Self-reported data is a significant limitation of snowball sampling. Participants provide information about themselves and also refer other people in their networks; thus, the accuracy of the data depends almost entirely on their honesty and memory. Self-reporting is susceptible to bias, as others may knowingly or inadvertently manipulate information at the expense of social desirability, fear of disclosure or their own perception. This is especially problematic in studies of sensitive topics, such as substance abuse or mental health, where study participants may downplay or exaggerate their histories. Without an objective means to verify this information, it is not clear how researchers can determine whether the data they've collected is legitimate.

A major limitation of snowball sampling includes its limited geographic representativeness. Participant recruitment happens within personal networks, which often results in participants coming from the same or closely linked geographic area. This effect means the sample is not diversity of cases, thus it is difficult to extend the findings to a bigger group of people. Snowball sampling further tends to inflate the representation of socially active and well-connected individuals while underrepresenting the isolated. However, snowball sampling still serves as a useful approach when traditional sampling methods are not feasible. To minimize its drawbacks, researchers can integrate it with other methods, including stratified sampling or mixed-methods approaches, so as to enhance the validity and representativeness of the results they obtain.

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References

Aldridge, Z., McDermott, H., Thorne, N., Arcelus, J., & Witcomb, G. L. (2024). Social Media Creations of Community

- and Gender Minority Stress in Transgender and Gender-Diverse Adults. *Social Sciences*, 13(9). <https://doi.org/10.3390/socsci13090483>
- Brannon, T. N., & Lin, A. (2021). "Pride and prejudice" pathways to belonging: Implications for inclusive diversity practices within mainstream institutions. *American Psychologist*, 76(3), 468-501. <https://doi.org/10.1037/amp0000643>
- Budge Stephanie, L., Katz-Wise, S. L., Tebbe, E. N., Howard, K. A.S., Schneider, C. L., & Rodriguez, A. (2012). Transgender Emotional and Coping Processes: Facilitative and Avoidant Coping Throughout Gender Transitioning. *The Counseling Psychologist*, 41(4), 601-647. <https://doi.org/10.1177/0011000011432753>
- Buss, J., Le, H., & Haimson, O. L. (2021). Transgender identity management across social media platforms. *Media, Culture and Society*, 44(1), 22-38. <https://doi.org/10.1177/0011000011432753>
- Craig, S. L., Eaton, A. D., McInroy, L. B., Leung, V. W.Y., & Krishnan, S. (2021). Can Social Media Participation Enhance LGBTQ+ Youth Well-Being? Development of the Social Media Benefits Scale. *Social Media+ Society*, 7(1). <https://doi.org/10.1177/2056305121988931>
- Craig, S. L., McInroy, L. B., McCreedy, L., & Alaggia, R. (2015). Media: A Catalyst for Resilience in Lesbian, Gay, Bisexual, Transgender, and Queer Youth. *Journal of LGBT Youth*, 12(3). <https://doi.org/10.1080/19361653.2015.1040193>
- Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, 16, 297-334. <https://doi.org/10.1007/BF02310555>
- Galupo, M. P., Henise, S. B., & Davis, K. (2014). Transgender microaggressions in the context of friendship: Patterns of experience across friends' sexual orientation and gender identity. *Psychology of Gender Orientation and Gender Diveristy*, 1(4), 461-470. <https://doi.org/10.1037/sgd0000075>
- Hammack, P. L., & Manago, A. M. (2024). The Psychology of Sexual and Gender Diversity in the 21st Century: Social Technologies and Stories of Authenticity. *American Psychologist*. <https://doi.org/10.1037/amp0001366>
- Herrmann, L., Barkmann, C., Bindt, C., Hohmann, S., Fahrenkrug, S., & Becker-Hebly, I. (2024). How social is social media for transgender and gender-diverse youth? Association of online social experiences with internalizing mental health problems. *European Child and Adolescent Psychiatry*, 33, 3503-3516. <https://doi.org/10.1007/s00787-024-02396-9>
- Kaiser, H. F. (1960). The Application of Electronic Computers to Factor Analysis. *Educational and Psychological Measurement*, 20(1), 141-151. <https://doi.org/10.1177/001316446002000116>
- Man, C. (2020). *Continuum*. Penguin Random House.
- McFadden, C., & Henry, M. C. (2017). 'My People': the potential of LGBT employee networks in reducing stigmatization and providing voice. *The International Journal of Human Resource Management*, 29(5), 1056-1081. <https://doi.org/10.1080/09585192.2017.1335339>
- Miller, R.A., Vaccaro, A., Kimball, E., & Forester, R. (2020). "It's Dude Culture": Students With Minoritized Identities of Sexuality and/or Gender Navigating STEM Majors. *Journal of Diversity in Higher Education*, 14(3), 340-352. <https://doi.org/10.1037/dhe0000171>
- Selkie, E., Adkins, V., Masters, E., Bajpai, A., & Shumer, D. (2020). Transgender Adolescents' Uses of Social Media for Social Support. *Journal of Adolescent Health*, 66(3), 275-280. <https://doi.org/10.1016/j.jadohealth.2019.08.011>
- Tetreault, P. A., Fette, R., & Meidlinger, P. C. (2013). Perceptions of Campus Climate by Sexual Minorities. *Journal of Homosexuality*, 60(7), 947-964. <https://doi.org/10.1080/00918369.2013.774874>
- Tobias, S., & Carlson, J. E. (2010). Brief report: bartlett's test of sphericity and chance findings in factor analysis. *Multivariate Behavioral Research*, 4(3), 375-377. https://doi.org/10.1207/s15327906mbr0403_8
- Tuck, A. B., & Thompson, R. J. (2023). The Social Media Use Scale: Development and Validation. *Assessment*, 31(3), 617-636. <https://doi.org/10.1177/10731911231173080>