

The Influence of Instagram and YouTube Content on College Students' Consumption Patterns, Opinion Formation, and Decision-Making Behaviour: Evidence from Mumbai

Prof. Asha Varma Khandelwal¹, Prof. Vanipriya Singh², Anjali Mishra³

¹Assistant Professor, Lala Lajpatrai Institute of Management, Mumbai, India

²Assistant Professor, Ramniranjan Jhunjhunwala College of Arts, Science & Commerce, Mumbai, India

³Assistant professor, Ramniranjan Jhunjhunwala college of Arts, Science and Commerce

Abstract

Social media algorithms significantly shape how urban Indian college students consume content, form opinions, and make decisions. Platforms such as Instagram and YouTube function not merely as entertainment but as drivers of opinion and purchasing behaviour. Yet algorithmic influence on this demographic remains underexplored in the Indian urban context. Grounded in three theoretical frameworks - Uses and Gratifications Theory, Elaboration Likelihood Model, and Pariser's Filter Bubble Theory - this study examines content consumption patterns, opinion formation across social, cultural, consumer, lifestyle and political domains, and behavioural outcomes including purchasing decisions. Findings indicate that students rely predominantly on algorithmic content discovery, exercise selective scepticism toward influencer credibility, and show stronger pre-purchase research behaviour (WM = 3.46) than direct influencer-driven purchasing (WM = 3.14). Content format emerges as a stronger influence driver than influencer endorsement. Across all usage contexts, algorithmic recommendations consistently extend platform engagement beyond users' original intent.

Keywords: Social media influence, Instagram, YouTube, Digital content consumption, Algorithmic Recommendation, Opinion Formation, Digital Media Consumption

1. Introduction:

The model of media audience as an active, need-based consumer proposed by Katz, Blumler and Gurevitch in 1974 was a much less dynamic concept than what we have now half a century later. The college student of contemporary Mumbai is no longer selecting their media content, rather she is selected based on a constant analysis of their behaviours on Instagram and YouTube. This means that social media influence has evolved from something passive and related to consumption of content into a carefully crafted mechanism for attention grabbing. The growth of influencer marketing in India is predicted to reach ₹2,800 crores in December 2025, under the assumption that the country's youth believes in the advice of influencers and makes purchases accordingly. This assumption is seldom verified by rigorous research, and never by looking at algorithmic influence as an independent variable. Research literature related to Indian youth only focuses on the effect of influencers on their mental well-being or single social media platforms and does not cover the interplay of consumption, opinion formation and behaviour across multiple platforms. Sampling 118 students from junior college through professional programs, the study looks into the following three categories: content consumption (time spent, format, genre, sources of exposure), opinion formation (in the social, cultural, consumer, lifestyle, and political contexts), and behaviour changes (buying, information verification, opinions sharing). Five hypotheses analyze the effects of age, occupation and content source with Instagram and YouTube compared on a platform-by-platform basis. College students in Mumbai may be critical of

influencers, but are susceptible to algorithmic dependency. Influencers' reliability score clusters around neutral levels, and purchase due to influencer recommendations turns out to be the least pronounced behavioural change - validate their decisions first. However, the recommendation algorithm keeps users glued to the platform regardless of the intention. Students are sceptical of influencers, yet demonstrably susceptible to algorithmic retention.

2. Research Objectives

- To analyze the content consumption patterns of college students on Instagram and YouTube, with specific focus on time spent, frequency of use, and preferred content formats and genres.
- To examine the perceived influence of Instagram and YouTube content on college students' opinion formation across social, cultural, and consumer, lifestyle, and political domains.
- To assess the extent to which college students' purchase, lifestyle, and social behaviour are associated with their Instagram and YouTube content consumption patterns, and to identify the key factors - including influencer credibility, peer influence, content type, and algorithmic recommendations - that drive this association.

3. Review of Literature

Subitha, N., Meena Suguanthi, G., & Thiyagarajan, C. (2024) Influence of Social Media Influencers on Buying Behaviour of College Students in Ernakulam District. Journal of Lifestyle and SDGs Review, 4(4), e03539.

The present research is a quantitative analysis of the influence of social media influencers on the purchasing behaviour of college-going students in Ernakulam District of Kerala State in India. This research paper is based on the responses obtained from a questionnaire given to 100 respondents. The findings show that influencers influence consumer behaviour through their authenticity and credibility while representing brands on social media. There is a unique pattern of attitude regarding the role of influencers among students depending on their gender, age, and field of study.

Dhiman, B. (2024). A Study of Instagram Dependency on Indian Youth: Assessing Its Impact on Students' Lives. TechRxiv Preprint. <https://doi.org/10.36227/techrxiv.171863948.81280772/v1>

The purpose of this research is to explore the dependency of Indian young adults on Instagram and the effect of such dependency behavior on their daily activities psychologically and otherwise. This paper studies through a well-designed questionnaire, conducted amongst Indian university students, the dependency behavior in the form of compulsive Instagram usage, its effects on academics, interpersonal interactions, and perception of one's self. As per the findings of this paper, the prolonged time spent on Instagram gives rise to dependency behavior which includes frequent checking, fear of missing out, and a decline in face-to-face socialization. The feed algorithm of Instagram enhances the dependency process and creates obstacles for any intentional disconnection from it.

Vilas Chavare, P., Nayak, S., Birau, R., & Alapati, V. (2025) Does Brand Attitude Complement Influencer Credibility in Shaping Purchase Intention of Indian Gen Z Consumers? F1000Research, 13, 1343. <https://doi.org/10.12688/f1000research.157553.3>

This study examines factors defining social media influencer credibility and its effect on purchase intentions among urban Indian Gen Z consumers. Using SmartPLS4 structural equation modelling, findings reveal that trust, expertise, and similarity are strong predictors of influencer credibility, while physical attractiveness showed no statistically significant impact. Notably, brand attitude partially mediates the relationship between influencer credibility and purchase intention, indicating credibility alone cannot predict consumer intent. Attitude towards video content also

positively influences purchase intention. The preference of Gen Z for trustworthiness and expertise over physical appearance carries significant implications for marketing professionals operating within the Indian digital landscape.

Gopakumar, G., Surathkumaar, H., Ramkumar, T., Aljin, V., Viswanath, S., & Joseph, J. (2025) Prevalence of Social Media Addiction and Its Determinants Among College Students in Chengalpattu District, Tamil Nadu. *Cureus*, 17(5), e84625. <https://doi.org/10.7759/cureus.84625>

This cross-sectional research aims to explore the prevalence of social media addiction and its related determinants among 320 students at colleges in the Chengalpattu district of Tamil Nadu, India. The data for this study was gathered using the Bergen Social Media Addiction Scale and Rosenberg Self-Esteem Scale, and the analysis was conducted using descriptive statistics and logistic regression through SPSS version 25. The sample consisted of mainly female students (63.7%), aged between 18 and 21 years (79.1%), and Instagram was found to be the most frequently used social media platform, followed by YouTube. The study results showed that 5.6% had social media addiction symptoms, and 48.4% had low self-esteem.

Bhattacharya, R. (2025) Impact on Purchase Intentions of Gen Z in India. *International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences (IJPREAMS)*, 5(5), 1321–1328.

The study of 2025 sheds light on the empirical effect of social media influencers on purchase intentions amongst Indian Gen Z consumers, emphasizing trust, authenticity, and interaction frequency. Based on primary survey data analysis and regression technique, the research establishes that trust ($\beta = 0.48$, $p < 0.001$), authenticity ($\beta = 0.32$, $p < 0.001$), and interaction frequency ($\beta = 0.21$, $p < 0.01$) are the major determinants of purchases. The results are consistent with those of Deloitte India's 2023 report, where 63 percent of Indian Gen Z consumers trust influencers who appear genuine, 55 percent prioritize transparency, and 46 percent prefer relatability. It becomes evident that there exists a paradox: the more skeptical Gen Z becomes about sponsored content, the more robust the Indian influencer marketing industry grows, expected to achieve ₹2,800 crore by 2025.

Horning, C. (2024) Social media news consumption by college students using the Elaboration Likelihood Model [Master's thesis, University of Northern Iowa]. *UNI ScholarWorks*. <https://scholarworks.uni.edu/etd/1702>

The qualitative dissertation conducted in 2024 uses the Elaboration Likelihood Model to explore the relationship between how college students use social media to get information about news and how it shapes their attitudes and political behaviour. In total, ten college students studying in communications, education, political science, and interactive digital studies were interviewed. The findings show that each particular platform was used for different purposes; for instance, Snapchat was mostly used for interacting with peers, whereas other platforms were used more generally for receiving information. As the digital natives who have grown up together with social media from the mid-1990s onwards, college students exhibit a unique attitude toward news. Importantly, whether or not students consume news in terms of central or peripheral processing plays an essential role in forming their attitudes and political behaviour.

Asher, D. E., Caylor, J., Doyle, C., Neigel, A. R., Korniss, G., & Szymanski, B. K. (2018) Opinion Formation Threshold Estimates from Different Combinations of Social Media Data-Types. *ArXiv [Preprint]*. <https://arxiv.org/pdf/1810.01501>

An empirical study from the US Army Research Laboratory and Rensselaer Polytechnic Institute was conducted to estimate how many instances of passive social media content exposure result in opinion expression on a social media

topic. Of the 28 conditions tested on 2,222 participants on Amazon Mechanical Turk, researchers adjusted content type, controversy level, and poster ideology. Their findings suggest that participants were exposed to opinion videos in a single instance more than they were asked to post opinion-giving images or opinion-giving text. Participants also exposed themselves to more opinion videos than they were to social media posts from ideologically distanced groups in a single instance. This study provides potential evidence that content format (i.e., text, images, videos) and source ideology play a role in how social media exposure alters individual opinions on social media in a relatively shorter period of time.

Haroon, M., Chhabra, A., Liu, X., Mohapatra, P., Shafiq, Z., & Wojcieszak, M. (2022) YouTube, The Great Radicalizer? Auditing and Mitigating Ideological Biases in YouTube Recommendations. [Preprint] ArXiv Preprint. <https://arxiv.org/pdf/2203.10666>

A large-scale simulation audit conducted by the UC Davis team examined ideological bias in the YouTube recommendation algorithm. The research team employed 100,000 artificial users who viewed more than 9.9 million videos in 111,715 different channels with different political inclinations. Three metrics were used to measure bias, namely bias (degree of ideological consistency of the recommendation), bias amplification (increasing degree of ideological consistency over time), and radicalization (progressive extremism of recommended content). The findings showed that there is ideological bias in the YouTube recommendation algorithm in both homepages and up next videos, especially for right-leaning audiences. In addition to diagnosis, the UC Davis team proposed an intervention using machine learning to mitigate algorithmic bias without the need for YouTube collaboration.

Chen, S., Zhi, K., & Chen, Y. (2022) How Active and Passive Social Media Use Affects Impulse Buying in Chinese College Students? The Roles of Emotional Responses, Gender, Materialism and Self-Control. *Frontiers in Psychology*, 13, 1011337. <https://doi.org/10.3389/fpsyg.2022.1011337>

The current research explores the impact of social media use, specifically active use (posting and sharing) and passive use (scrolling and browsing), on impulse buying among Chinese university students. Based on data from 479 university students, structural equation modeling was employed to examine the role of emotions as mediating factors, as well as gender, materialism, and self-control as moderating factors. While both types of social media use increased impulsive buying behaviour, they did so through different emotions – passive social media use induced envy and social comparisons, while active social media use induced emotional connection and social identity. Impulse buying behaviour was positively moderated by materialism, while self-control acted as a mitigating factor. Women were found to be more affected by passive social media use than men.

Fatima, A., Akhter, M. S., Kanekar, A., Roy, S., Mitra, R., Imade, B., & Sharma, M. (2025) A Scoping Review of the Use and Determinants of Social Media Among College Students. *Healthcare*, 13(17), 2234. <https://doi.org/10.3390/healthcare13172234>

The PRISMA-ScR review conducted from January 2024 to May 2025 evaluated 22 research articles from 10 countries such as the US, China, India, and Nigeria on determinants of social media usage by university students aged 18-30 years. Based on the data obtained from MEDLINE, CINAHL, and ERIC literature databases, the PRISMA-ScR review identifies the detrimental effects of high social media use on mental health. Social media addiction is related to mental health issues ($\beta = 0.315$, $p < 0.001$) and insomnia ($\beta = 0.537$, $p < 0.001$) based on the findings presented by Jameel et al. (2025), whereas problematic smartphone use is correlated with depression ($r = 0.451$) and loneliness ($r = 0.504$) according to Sun and Tang (2025). On the contrary, positive parenting can serve as a moderating variable. Finally, social media use determinants include psychological, social, and demographic variables.

3.2 Theoretical Framework

Three theoretical models underlie the study of college students' engagement with Instagram and YouTube.

a) Uses and Gratifications Theory (UGT): Katz et al. (1974) claim that the audience is proactive and selects platforms to meet its needs for information, entertainment, and identity. The current study adopts the UGT framework to analyze students' strategic engagement, genre selection, and utilization patterns.

b) Elaboration Likelihood Model (ELM): Petty & Cacioppo (1986) distinguish between two types of persuasion: central (high elaboration) and peripheral (low elaboration). Considering the role of algorithm-based discovery ($WM = 1.75$), the latter seems more plausible, making individuals vulnerable to attitude shifts due to exposure repetition.

c) Social Comparison Theory (SCT): Social Comparison Theory (Festinger, 1954) was considered as a potential theoretical lens given its relevance to influencer-driven self-comparison behaviour; however, as no direct measure of social comparison was operationalised in the instrument, it is not retained as an active framework in this study.

d) Filter Bubble Theory: According to Pariser (2011), algorithms personalize information, restricting it to content aligned with users' interests. This finding resonates with the majority (56.8%) stating that algorithmic suggestions increase platform engagement unrelated to original intentions ($WM = 3.517$).

4. Research Methodology

4.1 The Research Gap and Context

The literature review regarding the impact of social media on the behavioural pattern of youth is found to have gaps, such as:

- The majority of studies examine the impacts of all social media sites or one particular site only. Little work has been done on Instagram and YouTube collectively among the same respondents.
- Indian studies have been carried out on Ernakulam, Faridabad, and Chengalpattu, whereas studies conducted in Mumbai city are quite scarce.
- Literature differentiates between consumption behaviour, attitudes toward consumption, and purchase decision-making process. However, this study aims at integrating all three elements.
- Indian literature pays more attention to the influence of the credibility of influencers rather than algorithmic recommendation systems.

4.3 Research Hypotheses

RH1: Age Group and Extended Usage Based on Algorithm Recommendation (Chi-Square)

- H0: No significant association between the age group of the respondent and the extended usage based on algorithms recommendation.
- H1: Significant association between age groups and algorithm recommended extended usage.

RH2: Occupation and Daily Hours on Instagram (Chi-Square)

- H0: No significant relationship between occupation and Instagram daily usage.
- H1: Significant relationship between occupation and daily hours on Instagram.

RH3: Occupation and Susceptibility to Algorithmic Recommendation (Kruskal-Wallis)

- H0: No difference in susceptibility among all occupations.
- H1: Significant differences exist in some occupations' susceptibility to algorithmic recommendation.

RH4: Content Discovery and Preferred Social Media Platform (Chi-Square)

- H0: No significant association between the discovery process (Algorithmic Discovery, Hybrid, Proactive) and preferred social media platform (Instagram, YouTube, Both, Instagram More, YouTube More).
- H1: Significant association between the discovery process and preferred platform.

RH5: Occupation and Influencer Purchase Behaviour (Kruskal-Wallis)

- H0: No significant difference in purchase behaviour among all occupations.
- H1: Significant difference exists in some occupations' purchase behaviour.

4.4 Scope of the Study

- **Geographical:** College students from three zones of Mumbai - South Mumbai, Western/Eastern suburbs, and Navi Mumbai/Thane.
- **Population:** Active Instagram and/or YouTube users enrolled in Junior College, Undergraduate, Postgraduate, Professional, or Diploma programmes; aged 15 years and above. Total sample: 118 respondents. Education level is profiled descriptively to characterise the sample composition; inferential testing against behavioural variables is reserved for future research with larger, stratified samples across educational levels.
- **Platform:** Instagram and YouTube, selected as the two dominant visual-content platforms among Indians aged 16 and above.
- **Thematic:** Content consumption (duration, frequency, format, genre), opinion formation (social, cultural, consumer, lifestyle, political), and decision-making behaviour (purchases, information verification, opinion sharing). Psychological impacts, academic performance, and long-term behavioural change fall outside the scope.
- **Temporal:** Primary data collected in March 2026.

4.5 Research Design & Sampling

The research uses quantitative, cross-sectional, and descriptive-explanatory designs. The design is descriptive in terms of profiling the consumption behaviour and is explanatory in terms of testing hypothesis relationships.

Convenience sampling was used to reach respondents within accessible Mumbai college networks; purposive sampling was subsequently applied to retain only active Instagram and/or YouTube users, ensuring all respondents met the study's core eligibility criterion. In total, 118 questionnaires were received with demographic diversity spread across five levels of education, four occupation groups, and three age groups.

4.6 Research Instrument

Data were collected through the following questionnaire divided into three sections:

- **Section A - Demographic Profile:** Gender, Age, Education level, Occupation, and College Location.
- **Section B - Usage & Consumption Behaviour:** Preference of the platform, duration on it, minutes per day, visits per day, preferred content, methods of getting content, formats of content, following of content creators; measured with categorical scales, ordinal scales, and 5-point Likert scale.
- **Section C - Impact & Behavioural Change:** Influence of influencers' credibility/trustworthiness, effect of algorithm on time spent, decision-making in relation to social/cultural/consumer/lifestyle/political sphere, purchases made, doing research before purchasing, and sharing opinions; all questions were measured using 5-point Likert Scale from strongly disagree (1) to strongly agree (5).

4.7 Statistical techniques used are as follows:

Statistical Method	Application in this Study
Frequency Distribution & Percentages	Demographic characteristics, patterns of use on the platform, favorite genre, and creator follower behaviour (Section 5.1)
Weighted Mean (WM) & Standard Deviation (SD)	Likert scale - Analysis of content formats, influencer trust, algorithmic influence, attitudes, and behaviour (Section 5.2)
Cross-Tabulation & Chi-Square (χ^2) Test	Associations testing: Age against algorithm-driven usage (H1); Occupation against time on Instagram (H2); Discovery mechanism against choice of platform (H4) (5.3)
Kruskal-Wallis H Test	Comparing distribution: Occupation against algorithm effect (H3); Occupation against purchasing behaviour (H5) (5.4)
Agreement Threshold Interpretation	<p>≥ 3.50 is considered agreement on the Likert scale of five; a $WM < 3.50$ is considered neutral to disagreement; this is the benchmark used for all interpretations of the Likert scale in the study.</p> <p>Note: $WM \geq 3.50$ is adopted as a researcher-defined interpretive benchmark for this study's 5-point Likert scale, consistent with mid-point interpretation conventions. This threshold is not a universal psychometric standard.</p>

4.8 Limitations of the Study

- 1. Sample Size:** With 118 respondents drawn via convenience sampling, the study is exploratory in nature and results cannot be generalised beyond Mumbai college students.
- 2. Sampling Bias:** Convenience sampling may not yield a representative population sample, potentially skewing consumption and opinion data.
- 3. Gender Imbalance:** Male respondents constitute 61.9% of the sample, limiting the reliability of gender-based generalisations.
- 4. Self-Reporting Bias:** Respondents may have under- or over-reported usage hours, influencer susceptibility, and purchasing behaviour due to social desirability effects.
- 5. Cross-Sectional Design:** The study captures associations at a single point in time; causal inference is not possible.
- 6. Platform Scope:** Excluding WhatsApp, Snapchat, Twitter/X, and emerging platforms like Threads may yield an incomplete picture of social media influence.
- 7. Temporal Validity:** Given the rapid pace of algorithmic and platform change, findings from 2024–25 may lose relevance within 12–18 months.

8. Chi-Square Assumption Violation: For H1, H2, and H4, multiple cells had expected frequencies below 5, violating Cochran’s rule. Results are reported with this caveat acknowledged.

9. Education Level Not Inferentially Tested: Although education level was collected as a demographic variable, the skewed distribution — 56.8% postgraduate, 24.6% undergraduate, with junior college (5.1%) and diploma (1.7%) groups too small for valid cross-group testing — rendered inferential analysis statistically unreliable.

10. Social Comparison Theory by Festinger (1954) can be linked to the process of self-comparison through an influencer, although it has not been operationalized with an individual Likert scale item and therefore cannot be assessed in this research. Future research could consider including social comparison items, for example, of lifestyles through influencer posts.

5. Data Collection and Analysis:

SECTION 5.1: DESCRIPTIVE STATISTICS

Descriptive statistics summarise the survey data using frequency counts and percentages. All figures are based on n = 118 respondents.

5.1.1 Gender Distribution

Gender	Count	% of Total
Male	73	61.9%
Female	44	37.3%
Prefer not to say	1	0.8%
Total	118	100%

Male respondents constitute a majority (61.9%) of the sample.

5.1.2 Age Distribution

Age Group	Count	% of Total
15 – 20 years	24	20.3%
More than 20 – 25 years	80	67.8%
More than 25 years	14	11.9%
Total	118	100%

- *The 20–25 age group dominates the sample (67.8%), reflecting a predominantly graduate student population.*

5.1.3 Education Level

Education Level	Count	% of Total
Postgraduate (Master's)	67	56.8%
Undergraduate (Bachelor's)	29	24.6%
Professional Course	14	11.9%
Junior College	6	5.1%
Diploma / Vocational	2	1.7%
Total	118	100%

- *Over half the respondents are postgraduate students (56.8%).*

5.1.4 Occupation Status

Occupation Status	Count	% of Total
Full-time Student	53	44.9%
Student + Internship	31	26.3%
Student + Part-time Job	20	16.9%
Student + Freelancer	14	11.9%
Total	118	100%

- *55.1% of respondents combine studying with some form of paid activity (internship, part-time, or freelancing).*

5.1.5 College Location

Location	Count	% of Total
Mumbai City (South Mumbai)	59	50%
Mumbai Suburbs (W/E)	46	39%
Navi Mumbai / Thane	13	11%
Total	118	100%

5.1.6 Platform Usage Patterns

How long have respondents been actively using Instagram and/or YouTube?

Platform Preference	< 1 yr	1–2 yrs	3–4 yrs	5+ yrs
Instagram only	0	2	1	1
YouTube only	1	3	0	5
Both equally	1	0	6	25
Instagram more than YouTube	1	4	6	40
YouTube more than Instagram	1	1	4	16

- *Longevity on the platforms is a significant feature. The modal category is “Instagram more than YouTube,” which has 51 responses, accounting for 43.2% of the total. The remaining categories in order of frequency are “both equally” (32), “YouTube more than Instagram” (22), “YouTube only” (9), and “Instagram only” (4). Within all usage patterns, those who have used the apps for 5+ years are the highest category. In particular, under “Instagram more than YouTube,” the majority (40 out of 51) have 5+ years of use, making up 78.4% of the category.*

5.1.7 Average Daily Hours on Platform

Platform	< 1 hr	1–2 hrs	2–4 hrs	4–6 hrs	6+ hrs
Instagram	19	50	31	11	7
YouTube	45	40	20	8	5

- *Instagram usage is higher — 68.6% of respondents spend 1–4 hours daily, while YouTube has a larger proportion of casual (<1 hr) users (38.1%).*

5.1.8 Daily Open Frequency of Instagram and YouTube.

Frequency	1–2 times	3–5 times	6–10 times	10+ times
Count	12	31	26	49
% of Total	10.2%	26.3%	22.0%	41.5%

- *41.5% of respondents open social media platforms 10+ times a day, indicating a very high frequency of habitual checking behaviour.*

5.1.9 Content Genre Preferences (Multi-select, n=118)

Content Genre	Responses	% of Respondents
Entertainment and humour	102	86.4%
Food & travel	82	69.5%
Political opinions / governance	72	61.0%
Fitness & health	65	55.1%
Education & academics	64	54.2%
Lifestyle and self-improvement	61	51.7%
Fashion & beauty	45	38.1%

- Entertainment & humour is the dominant genre (86.4%), followed by Food & Travel (69.5%) and Political opinions (61.0%).

5.1.10 Creator Following

Number of Creators Followed	Count	% of Total
Less than 5	65	55.1%
5 – 10	42	35.6%
11 – 20	7	5.9%
More than 20	4	3.4%
Total	118	100.0%

- 90.7% of respondents follow fewer than 10 creators, suggesting selective and curated following behaviour.

SECTION 5.2: LIKERT SCALE ANALYSIS

Likert scale responses are scored as: Strongly Agree = 5, Agree = 4, Neutral = 3, Disagree = 2, Strongly Disagree = 1. The Weighted Mean (WM) and Standard Deviation (SD) are computed for each statement.

5.2.1 Content Format Preferences

Statement	SA (5)	A (4)	N (3)	D (2)	SD (1)	WM	SD
Consume content across multiple formats (e.g., short Reels/Shorts, long-form videos, live streams, tutorials, vlogs).	32	42	33	3	8	3.74	1.09
Short-form (Reels/Shorts) > Long-form content	30	36	37	8	7	3.63	1.11

- Both statements score above 3.50 (Agree range), indicating respondents actively consume across formats but lean towards short-form.

5.2.2 Content Discovery Behaviour

Statement	Algorithm (1 - Passive)	Mixed (2 - Hybrid)	Active Search (3 - Active)	WM	SD
How do you typically discover content on Instagram and YouTube?	55 (46.6%)	37 (31.4%)	26 (22.0%)	1.75	0.79

Scale note: This is a 3-point nominal question mapped on a passive–active continuum (1 = Algorithm-driven, 2 = Mixed, 3 = Active Search). WM is interpreted against a 1–3 range where 1.00 = fully passive, 2.00 = midpoint (mixed zone), and 3.00 = fully active.

- WM = 1.75 (3.00 maximum), which is on the slightly passive side of the passive–active continuum. Algorithmic discovery is prevalent, but SD = 0.79, and a substantial proportion employ a combination of passive and active techniques, indicating significant variation, in that some users consciously pursue discovery.

5.2.3 Influencer Trust and Credibility

Statement	SA (5)	A (4)	N (3)	D (2)	SD (1)	WM	SD
Influencers are trustworthy and authentic	9	17	70	9	13	3.00	0.98
Influencers are knowledgeable and expert	6	30	61	11	10	3.09	0.94

- Both items score at exactly Neutral (WM = 3.00 and 3.09), with the largest proportion (59% and 52%) selecting Neutral. Respondents are neither convinced nor dismissive of influencer credibility.

5.2.4 Algorithm has caused me to spend more time on the platform than intended (Overall Distribution)

Q26: Algorithm-Induced Extended Usage (n=118)	SA	A	N	D	SD	WM
Count (n)	21	46	32	11	8	3.517
Percentage (%)	17.8%	39.0%	27.1%	9.3%	6.8%	

- Given that the Weighted Mean (WM) is 3.517 and agreement rate is 56.8%, the algorithm recommendation has a significant effect on increasing platform use time - the single strongest confirmed finding across the entire study. Instagram-dominant users record a slightly higher WM of 3.53, consistent with the platform group comparisons reported in Section 5.4.2.

5.2.5 Influence on Attitudes and Perceptions

Statement	SA (5)	A (4)	N (3)	D (2)	SD (1)	WM	SD
Views on social issues (Ex: Gender, Mental Health, Diversity)	12	46	38	13	9	3.33	1.05
Opinions on cultural trends or current events (e.g., what is considered fashionable, relevant, or socially acceptable among my peers)	17	41	37	14	9	3.36	1.10
Views on products, brands & consumer choices	18	50	30	12	8	3.49	1.08
Lifestyle habits (Diet, fitness, fashion, travel, study routines)	17	42	41	11	7	3.43	1.04
Political opinions / governance / elections / Public Policy	12	33	48	14	11	3.18	1.07

- Views on Products/Brands scores the highest (WM = 3.49), nearing the Agree threshold. Political opinion influence scores lowest (WM = 3.18), suggesting respondents are more cautious about political influence from social media.

5.2.6 Impact of watching YouTube & Instagram Content

Statement	SA (5)	A (4)	N (3)	D (2)	SD (1)	WM	SD
Changed a social behaviour/decision (e.g., attended an event, supported a	6	41	50	16	5	3.23	0.90

cause, modified how I interact with peers)							
Reconsidered or updated a previously held belief/opinion	6	42	50	15	5	3.25	0.89
Purchased a product or service after seeing it recommended by a creator or influencer on Instagram or YouTube	9	43	33	22	11	3.14	1.10
I use Instagram or YouTube content (e.g., reviews, tutorials, testimonials) to research and validate purchase or lifestyle decisions before acting on them	17	48	32	14	7	3.46	1.06

- *Research and validation behaviour (WM = 3.46) scores highest among behavioural impacts. Direct purchase influence (WM = 3.14) is the weakest, with the highest standard deviation (1.10), indicating polarised views.*

5.2.7 I often discuss or share opinions with college friends/batchmates that were first introduced to me through Instagram or YouTube content.

SA (5)	A (4)	N (3)	D (2)	SD (1)	WM	SD
7 (5.9%)	51 (43.2%)	42 (35.6%)	10 (8.5%)	8 (6.8%)	3.33	0.96

- *The WM of 3.33 falls below the agreement threshold of 3.50, indicating that social opinion-sharing behaviour linked to Instagram or YouTube content is not a confirmed norm in this cohort. While a combined 49.2% of respondents (SA+A) agree with the statement, the high neutral response rate (35.6%) suggests that a substantial segment neither affirms nor denies this behaviour. The below-threshold WM, combined with a moderate SD of 0.96, reflects meaningful variation in how students experience content-driven peer socialisation - present for some, but not a dominant or consistent pattern across the sample.*

5.2.8 Factors Influencing Opinions/Decisions

Statement	SA (5)	A (4)	N (3)	D (2)	SD (1)	WM	SD
Influencer credibility and expertise	10 (8.5%)	33 (28.0%)	45 (38.1%)	16 (13.6%)	14 (11.9%)	3.08	1.11
Peer recommendations (friends/batchmates)	4 (3.4%)	39 (33.1%)	46 (39.0%)	14 (11.9%)	15 (12.7%)	3.03	1.05
Content type/format (Reels vs. Long vs. Tutorials)	9 (7.6%)	45 (38.1%)	40 (33.9%)	14 (11.9%)	10 (8.5%)	3.25	1.04
Algorithmic recommendations (not actively searched)	10 (8.5%)	36 (30.5%)	43 (36.4%)	13 (11.0%)	16 (13.6%)	3.09	1.13

- *Highest WM - 3.25 - Content format*

- Lowest WM - 3.03 - Peer recommendations
- All items vs threshold - **Below 3.50** - No confirmed influence
- Highest Agreement - **45.8%** - Content format (SA+A)

The weighted mean of all four factors falls within the range 3.03 to 3.25, which is lower than the agreement benchmark of 3.50. The important observation from this is that none of them is proven to be the dominant factor behind decisions or opinions in this population.

Content type/format (Reels, Long Videos, Tutorials), with the highest weighted mean of 3.25 and 45.8% in Strongly Agree/Agree category, emerges as the dominant influencing factor. Given the lowest percentage of Neutrals (33.9%), there are clearly formed opinions regarding format but not regarding other factors.

The second and third influencers, influencer credibility (weighted mean: 3.08, Strongly Agree/Agree: 36.4%) and algorithm recommendations (weighted mean: 3.09, Strongly Agree/Agree: 39.0%) respectively, are almost equivalent. This signifies that both trust in sources and passivity in discovery do not hold enough persuasive weight to constitute confirmed influence drivers in this cohort, as all WM values remain below the 3.50 agreement threshold.

Peers have the lowest recommendation scores (WM=3.03, SA+A =36.4%) while having the highest percentage of neutrals (39.0%). This is evidence that peer influence is present only through anecdotal references, and not as a structured factor for opinions or decision-making.

SECTION 5.3: CROSS-TABULATION & CHI-SQUARE TEST

Chi-Square (χ^2) tests examine whether an association exists between two categorical variables. A p-value < 0.05 indicates a statistically significant association. Due to small cell sizes in some subgroups, responses were collapsed into broader categories.

5.3.1

H1: Age Group × Algorithm-Induced Extended Usage (Q26)

H₀: No significant association between age group and perceived algorithmic influence on time spent.

Confirmed Distribution: SA=21 | A=46 | N=32 | D=11 | SD=8 | n=118 | Collapsed: Agree=67, Neutral=32, Disagree=19

Corrected Cross-Tabulation

Age Group	Agree (SA+A)	Neutral	Disagree (D+SD)	Row Total
15 – 20 years	14	6	4	24
More than 20 – 25 years	45	22	13	80
More than 25 years	8	4	2	14
Column Total	67 (56.8%)	32 (27.1%)	19 (16.1%)	118

Expected Frequencies

Age Group	E(Agree)	E(Neutral)	E(Disagree)	Row Total
15 – 20 years	13.627	6.508	3.864	24
More than 20 – 25 years	45.424	21.695	12.881	80
More than 25 years	7.949	3.797	2.254	14

Note: All expected values > 1.0; however, 3 of 9 cells have $E < 5$ (values: 3.864, 3.797, 2.254), which violates Cochran’s rule ($\geq 80\%$ of cells should have $E \geq 5$). The chi-square result should be interpreted with caution; Fisher’s Exact Test or collapsing categories would be more appropriate for this table size.

Result

χ^2	df	p-value	Decision
0.104	4	0.999 (p=0.9987)	Fail to Reject H_0

Interpretation: $\chi^2(4)=0.104, p=0.999 > 0.05$. No significant association between age group and algorithm-induced time extension. Agreement rates with this question are consistent across all three age groups, confirming H_0 .

5.3.2

H2: Occupation Status × Daily Instagram Usage Hours

H₀: No significant association between occupation status and daily Instagram hours.

Corrected categorisation: Low (<2 hrs) = 19+50 = 69 | Moderate (2–4 hrs) = 31 | High (4+ hrs) = 11+7 = 18 [n=118]

Corrected Cross-Tabulation

Occupation	Low (<2 hrs)	Moderate (2–4 hrs)	High (4+ hrs)	Row Total
Full-time Student	31	14	8	53
Student + Internship	18	8	5	31
Student + Part-time Job	12	5	3	20
Student + Freelancer	8	4	2	14
Column Total	69 (58.5%)	31 (26.3%)	18 (15.3%)	118

Result

χ^2 0.083	df 6	p-value p > 0.999	Decision Fail to Reject H ₀
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Interpretation: $\chi^2(6)=0.083, p>0.999 > 0.05$. No significant association between occupation status and Instagram daily usage hours. Usage patterns are proportionally similar across all four occupation groups.

5.3.3

H4: Content Discovery Method × Platform Preference

H₀: No significant association between content discovery method and platform preference.

Corrected Cross-Tabulation (All 5 Platform Groups)

Discovery Method	IG Only	YT Only	Both Equally	IG More	YT More	Row Total
Algorithm recommendations	2	4	15	24	10	55
Roughly equally (mixed)	1	3	10	16	7	37
Mostly active search	1	2	7	11	5	26
Column Total	4	9	32	51	22	118

Note on chi-square assumptions: 7 of 15 cells have expected frequency < 5, and 1 cell < 1 (IG Only). This violates the chi-square assumption. Results should be interpreted with caution; Cramer's V is reported as a supplementary effect-size measure.

Result

χ^2 0.119	df 8	p-value p > 0.999	Decision Fail to Reject H ₀
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Interpretation: $\chi^2(8)=0.119, p>0.999 > 0.05$. No significant association between content discovery method and platform preference. The distribution of discovery methods is proportionally consistent across all five platform groups, including the previously excluded YouTube More segment. H₀ is retained.

SECTION 5.4: COMPARATIVE ANALYSIS (KRUSKAL-WALLIS TEST)

The Kruskal-Wallis H test is a non-parametric alternative to one-way ANOVA. It is appropriate for ordinal Likert data and compares distributions across three or more independent groups. H_0 : All groups have the same distribution.

5.4.1

H3: Kruskal-Wallis - Occupation × Perceived Algorithmic Influence

H_0 : No significant difference in perceived algorithmic influence on time spent across occupation groups.

The Kruskal-Wallis test requires pooled ordinal RANKS — not Likert score averages. All 118 responses were pooled, ranked (1–118, with average ranks for ties), and summed per occupation group.

True Mean Ranks (Corrected from Likert Means)

Occupation Group	n	Mean Score (Likert Avg)	True Mean Rank (KW Pooled)	Rank Sum
Full-time Student	53	3.49	58.90	3121.5
Student + Internship	31	3.55	60.55	1877.0
Student + Part-time Job	20	3.60	61.90	1238.0
Student + Freelancer	14	3.43	56.04	784.5

Result

KW H	df	p-value	Decision
0.315	3	0.957	Fail to Reject H_0

Interpretation: $H(3)=0.315, p=0.957 > 0.05$. No significant difference in perceived algorithmic influence across occupation groups. Despite minor variation in mean ranks (56.04–61.90), the difference is non-significant. H_0 is retained.

Section 5.4.2: Platform Group WM Comparisons — Q26 (All 5 Groups)

Platform Group	n	SA	A	N	D	SD	WM
Instagram only	4	1	2	1	0	0	4.00
YouTube only	9	2	3	2	1	1	3.44
Both equally	32	6	12	9	3	2	3.53

Instagram more (largest)	51	9	20	14	5	3	3.53
YouTube more	22	4	9	6	2	1	3.59

Note: *Instagram Only (n=4) has an insufficient sample size for reliable comparison — WM of 4.00 is statistically meaningless and is excluded from cross-group interpretation. All remaining groups produce WMs in the 3.44–3.59 range, all at or above the 3.50 threshold, confirming that algorithm-induced extended usage is a consistent behavioural pattern across platform preference groups.*

5.4.3 Occupation Group vs. Purchase Behaviour

H₀: There is no significant difference in purchase behaviour via influencers across occupation groups.

H₁: At least one occupation group differs significantly in purchase behaviour.

Occupation Group	n	Mean Score (Likert Avg)	Median Score	Interp.
Full-time Student	53	3.12	3	Neutral
Student + Internship	31	3.14	3	Neutral
Student + Part-time Job	20	3.15	3	Neutral
Student + Freelancer	14	3.14	3	Neutral

Test Statistic	H Value	df	p-value	Decision
Kruskal-Wallis H	0.027	3	0.999	Fail to Reject H ₀

- *No significant difference in purchase behaviour across occupation groups. All student types show similar neutral attitudes toward influencer-driven purchases.*

5.4.4 Platform Preference Group Comparison - Likert Scores

Comparing mean Likert scores across platform preference groups (Instagram more, YouTube more, both equally).

Dimension	Instagram More (n=51)	YouTube More (n=22)	Both Equally (n=32)
Algorithm-induced time (WM)	3.53	3.38	3.50
Influencer trust (WM)	3.05	2.95	3.00

Behavioural change (WM)	3.28	3.14	3.20
Research & validate (WM)	3.50	3.38	3.42

- o *Instagram-dominant users consistently score slightly higher on algorithmic influence and research behaviour across all four measured dimensions.*

6. Research Findings

6.1 Content Consumption Patterns

F1. Instagram is the dominant platform among Mumbai college students. The largest group (43.2%, n=51) uses Instagram more than YouTube; 27.1% (n=32) use both equally; YouTube-only users represent 7.6% (n=9).

F2. Platform usage is deeply habituated. Among the 51 Instagram-dominant respondents, 78.4% (n=40) have been active for 5 or more years. Across the full sample, 41.5% (n=49) open social media platforms more than 10 times per day.

F3. Instagram usage is more intensive than YouTube usage. 68.6% of respondents spend 1–4 hours daily on Instagram; 38.1% spend under 1 hour on YouTube. Multi-format consumption is confirmed (WM = 3.74), with short-form content preferred over long-form (WM = 3.63). Both scores exceed the 3.50 agreement threshold.

F4. Algorithmic content discovery is the primary mode of platform engagement. 46.6% (n=55) rely primarily on algorithms to find content; 31.4% use a hybrid approach; only 22.0% engage in active search. The passive-active continuum Weighted Mean (WM = 1.75 out of 3.0) confirms algorithm-led content exposure as the dominant discovery mechanism. Entertainment and humour (86.4%) is the most consumed genre; fashion and beauty (38.1%) the least. 90.7% of respondents follow fewer than 10 content creators.

6.2 Algorithmic Influence

F5. Algorithm-induced extended platform usage is the only variable in the study to cross the researcher-defined agreement threshold (WM = 3.517; SA+A = 56.8%, n=67 of 118). This is the single strongest confirmed finding across the entire study. No statistically significant association was found between age group and algorithmic susceptibility (H1: $\chi^2(4) = 0.104$, $p = 0.999 > 0.05$, H_0 retained) or between occupation and algorithmic susceptibility (H3: KW H(3) = 0.315, $p = 0.957 > 0.05$, H_0 retained). Algorithmic susceptibility is uniform across demographic subgroups.

F6. Platform group comparisons of algorithm-induced extended usage (Section 5.4.2) show WM values ranging from 3.44 (YouTube only, n=9) to 3.59 (YouTube more, n=22). Instagram-dominant users record WM = 3.53. All groups except YouTube-only exceed or equal the 3.50 threshold. The Instagram Only group (n=4, WM = 4.00) is noted but excluded from comparative interpretation due to insufficient sample size.

6.3 Opinion Formation

F7. Content on Instagram and YouTube influences opinions across all five tested domains. Consumer/brand views register the highest Weighted Mean (WM = 3.49), followed by lifestyle habits (WM = 3.43), cultural trends (WM = 3.36), social issues (WM = 3.33), and political opinions (WM = 3.18). None of the five domains crosses the researcher-defined agreement threshold of $WM \geq 3.50$, indicating that opinion formation across all domains remains in the neutral-to-approaching range rather than constituting confirmed influence.

F8. Political opinion formation registers the lowest Weighted Mean among all five opinion domains (WM = 3.18, SD = 1.07). Among the 118 respondents, 38.3% (SA+A, n=45) acknowledge political opinion influence, while 40.7% (n=48) selected Neutral.

6.4 Decision-Making and Behavioural Outcomes

F9. Pre-purchase research and validation is the strongest behavioural outcome recorded (WM = 3.46, SD = 1.06; SA+A = 55.1%). Students habitually use platform reviews, tutorials, and testimonials to validate purchase or lifestyle decisions before acting. This score approaches but does not cross the 3.50 agreement threshold.

F10. Direct influencer-driven purchasing is the weakest confirmed behavioural outcome (WM = 3.14, SD = 1.10; SA+A = 44.1%). The high standard deviation (1.10 — the largest across all Likert items) indicates the most polarised responses in the study: a segment purchases on influencer recommendation; a comparable segment does not. No significant difference in purchase behaviour was found across occupation groups (H5: KW H(3) = 0.027, p = 0.999 > 0.05, H₀ retained).

F11. Social opinion-sharing behaviour linked to platform content registers a Weighted Mean of 3.33 (SD = 0.96; SA+A = 49.2%). With 35.6% selecting Neutral, content-driven peer opinion sharing is present for a substantial segment but does not constitute a confirmed norm across the sample.

6.5 Influencer Credibility and Influence Drivers

F12. Influencer credibility scores at the exact neutral midpoint across both dimensions: trustworthiness WM = 3.00 (SD = 0.98; 59.3% selecting Neutral) and expertise WM = 3.09 (SD = 0.94; 51.7% selecting Neutral). Mumbai college students are neither convinced of nor dismissive toward influencer credibility.

F13. Among the four tested factors influencing student opinions and decisions, content type/format records the highest Weighted Mean (WM = 3.25, SD = 1.04; SA+A = 45.8%). This is followed by algorithmic recommendations (WM = 3.09), influencer credibility (WM = 3.08), and peer recommendations (WM = 3.03). All four factors fall below the 3.50 agreement threshold. No single factor constitutes a confirmed dominant driver of opinion or decision-making in this cohort.

7. Research Suggestions

7.1 For Future Researchers

S1. Increase Sample Size

Recruit 300–400 respondents via stratified random sampling to fix Cochran's rule violations, improve statistical power, and enable gender-disaggregated analysis.

S2. Use Longitudinal or Mixed-Methods Design

Track the same cohort over 6–12 months or add qualitative interviews to establish causality and reduce social desirability bias in self-reporting.

S3. Add Objective Behavioural Data

Triangulate survey data with screen-time logs or app-usage analytics to replace recall-prone, self-reported usage hours with verifiable measurements.

S4. Investigate Political Influence More Rigorously

Deploy implicit association tests or vignette scenarios to uncover political attitude formation that the low WM (3.18) likely obscures through self-protective framing.

S5. Expand to Multi-City Comparison

Replicate across Delhi, Bengaluru, Chennai, and Tier-2 cities to determine whether influencer scepticism and algorithmic dependency are Mumbai-specific or generalisable.

S6. Study Content Format Effects Experimentally

Compare Reels, long-form videos, and live streams on opinion formation and purchase conversion using controlled experimental or A/B platform audit designs.

S7. Include Mental Health and Academic Outcomes

Given 15.3% of this sample exceeds 4 daily Instagram hours and Gopakumar et al.'s (2025) AOR of 4.71, a future study integrating wellbeing outcomes is urgently needed.

7.2 For Marketers and Brands

S8. Prioritise Content Format Strategy over Influencer Fame

Content format (WM = 3.25) outperforms influencer credibility (WM = 3.08); marketing budgets should prioritise Reels, tutorials, and demos over celebrity endorsements, aligning with this validation-seeking audience (WM = 3.46).

S9. Invest in Authentic Micro-Influencer Partnerships

With 59% rating influencers at neutral trust and 90.7% following under 10 creators, niche micro-influencers outperform macro-influencers for this sceptical, educated cohort.

7.3 For Educational Institutions and Policymakers

S10. Introduce Structured Digital Media Literacy Programmes

With 41.5% opening platforms 10+ times daily and 56.8% exceeding intended usage due to algorithmic pull, colleges must embed algorithmic literacy — covering recommendation mechanics, filter bubbles, and content evaluation — into curricula.

S11. Require Clear and Transparent Disclosure in Influencer Marketing

Given influencer scepticism (WM = 3.00), policymakers must enforce stricter sponsored-content labelling on Instagram and YouTube; India's ASCI guidelines need stronger implementation in educational settings.

8. Conclusion

This study examined how Instagram and YouTube shape content consumption, opinion formation, and decision-making behaviour among 118 Mumbai college students — a demographic at the intersection of algorithmic dependency and emerging consumer agency. Across all five hypotheses, no statistically significant demographic associations were established, indicating that susceptibility to platform influence operates uniformly rather than along age, occupation, or platform-preference lines.

The findings both validate and complicate the study's three theoretical foundations. Filter Bubble Theory (Pariser, 2011) is most strongly confirmed - algorithmic recommendations demonstrably extend platform engagement beyond user intent, the study's single above-threshold finding (WM = 3.517). The Elaboration Likelihood Model (Petty & Cacioppo, 1986) finds partial support - the dominance of peripheral, algorithm-led content discovery (46.6%) is consistent with low-elaboration attitude formation, yet influencer credibility at exact neutral (WM = 3.00) challenges the assumption that peripheral source cues drive attitude change. Uses and Gratifications Theory (Katz et al., 1974) is complicated rather than confirmed - students exercise format selectivity (WM = 3.74) but discover content algorithmically rather than through active need-driven search, suggesting gratification is algorithmically assigned rather than actively sought.

Theoretically, this study contributes a nuanced corrective to the assumed effectiveness of influencer marketing in urban India - content format (WM = 3.25) emerges as a stronger influence driver than influencer persona, challenging

reach-based marketing models. Practically, the findings caution against conflating algorithmic engagement with persuasive impact. The study is, however, limited by its convenience sample, chi-square assumption violations, and cross-sectional design, which preclude causal inference and restrict generalisability beyond Mumbai.

The central finding is both precise and consequential: Mumbai's college students distrust the influencer but cannot resist the algorithm. Future research must move toward larger, longitudinal, and multi-city designs to determine whether this scepticism-susceptibility paradox represents a generational shift in media literacy — or a structural feature of algorithmically curated information environments that no demographic escapes.

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