



THE DIGITAL TRAP: HOW SHORT POLITICAL VIDEOS ON TIKTOK AND REELS LOCK PAKISTANI YOUTH INTO ONE-SIDED THINKING

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Abstract

This study investigates how algorithm-driven short-form video platforms (e.g., TikTok, Instagram Reels) shape political perceptions and contribute to affective political polarization among Pakistani youth. A quantitative cross-sectional survey was conducted with a sample of 390 young adults (aged 18–30) in Lahore, Pakistan, selected using convenience sampling. Data were collected via a structured questionnaire measuring platform usage, exposure to algorithmically curated political content, and affective polarization. Descriptive statistics, chi-square tests of independence, and binary logistic regression were employed for analysis. Results indicate that 64.1% of respondents spend over three hours daily on short-form video platforms. A majority (57.2%) agreed that algorithms repeatedly show similar political viewpoints, leading to the perception of ideological echo chambers (46.9% rarely see opposing views). Logistic regression revealed that daily consumption of political short-form videos significantly predicts affective political polarization ($B = 1.43, p < .001$), with heavy users being over four times more likely to report heightened emotional attachment to political groups. The study confirms the existence of a "digital trap" where algorithmic personalization reinforces existing beliefs, limits exposure to diverse perspectives, and intensifies affective polarization. These findings have critical implications for media literacy interventions, platform governance, and democratic discourse in Pakistan.

Keywords: Short-Form Video, Algorithmic Personalization, Affective Political Polarization, Echo Chambers, Pakistani Youth, Digital Trap

1. Introduction

The transformation of political communication from traditional mass media to decentralized digital platforms has fundamentally altered how citizens, particularly youth, encounter and process political information. Unlike newspapers or television broadcasts, which historically offered a relatively standardized information diet, contemporary social media platforms leverage sophisticated recommendation algorithms to deliver hyper-personalized content. Among these, short-form video platforms such as TikTok and Instagram Reels have achieved unprecedented popularity, especially among young adults. These platforms, characterized by ephemeral, emotionally charged, and rapidly consumable content (typically under 60 seconds), have become primary sources of news and political commentary for a generation (Hussain, 2025).

The core mechanism driving engagement on these platforms is the algorithmic recommendation system, which analyses user behaviour (views, likes, shares, watch time, comments) to predict and serve content that maximizes retention. While this personalization enhances user experience, it also creates a significant socio-political risk: the formation of "filter bubbles" and "echo chambers" (Pariser, 2011). By selectively exposing users to information that aligns with their pre-existing beliefs and filtering out dissonant



perspectives, algorithms can inadvertently reinforce ideological rigidity and foster "affective polarization" a deep emotional division where political out-groups are viewed with hostility, transcending mere policy disagreement (Iyengar & Westwood, 2015).

In Pakistan, a nation with over 60% of its population under the age of 30 and rapidly increasing internet and smartphone penetration, the impact of this phenomenon is both acute and under-researched. The political landscape is volatile, and traditional media often faces pressures, making short-form video platforms a crucial, yet potentially polarizing, arena for political mobilization and discourse (Mirza et al., 2025). Recent events, including the 2024 general elections, saw the rise of the "TikTok Jalsa" (digital rally), demonstrating the immense power of these platforms to shape political narratives and mobilize youth (Riasat et al., 2025). However, this shift carries a price: the potential for algorithmic curation to exacerbate existing political schisms, entrench one-sided thinking, and undermine national dialogue (Iftikhar & Bajwa, 2025).

This study, therefore, addresses a critical gap in the literature by empirically examining the relationship between short-form video consumption, algorithmic personalization, and affective political polarization among Pakistani youth. We move beyond simple usage statistics to investigate the psychological mechanisms of selective exposure and heuristic processing within this specific digital ecosystem.

1.1 Research Objectives

The specific objectives of this study were:

1. To investigate the level of short-form political video consumption among Pakistani youth.
2. To examine how algorithmic recommendations shape political content exposure.
3. To analyse the relationship between short-form video consumption and affective political polarization.

1.2 Research Questions

The following research questions guided the investigation:

RQ1. How often do Pakistani youth consume political videos on short-form platforms?

RQ2. Do recommendation algorithms repeatedly show similar political viewpoints?

RQ3. Does exposure to short-form political videos influence emotional attitudes toward political groups?

1.3 Hypotheses

Based on the literature review and theoretical framework, the following hypotheses were formulated:

H1: Higher daily consumption of short-form video platforms is significantly associated with increased exposure to political content.

H2: A majority of young Pakistani users perceive that platform algorithms repeatedly show them similar political viewpoints, limiting exposure to opposing views (i.e., experiencing echo chambers).

H3: Frequent consumption of algorithmically curated political short-form videos is a significant positive predictor of affective political polarization among Pakistani youth.

2. Literature Review

2.1 The Anatomy of the Digital Trap

The "digital trap" refers to the self-reinforcing cycle where user interaction with personalized content leads to increasingly narrow and extreme information exposure (Ahmmad et al., 2025). Algorithms on platforms like TikTok are biased towards emotionally charged, high-arousal content that maximizes engagement (Cinelli et al., 2021). In the Pakistani context, this translates to the amplification of sensational political clips, dramatic montages of leaders, and confrontational "roast" videos targeting political opponents, which generate far more engagement than nuanced policy discussions (Khalil, 2024). This process creates an ideological mirror, reflecting and amplifying users' existing biases while systematically excluding dissenting opinions (Bakshy et al., 2015).

2.2 Psychological Mechanisms of One-Sided Thinking

The effectiveness of the digital trap is rooted in established psychological vulnerabilities.

Selective Exposure and Confirmation Bias: Selective exposure theory suggests that people tend to seek out information that confirms their current beliefs. Husnain and Tareen (2024) note that Pakistani youth often use short-form videos as a confirmation machine. Because these videos are typically under 60 seconds, they do not encourage deeper analysis but instead provide rapid dopamine hits of political approval. This leads



to ideological rigidity, where users see their chosen narrative as the complete truth and label opposing information as fake news or propaganda.

Heuristic Processing versus Systematic Thinking: Short-form videos encourage "heuristic processing," which allows users to make snap judgments based on emotional signals rather than careful analysis. When a user watches 50 political clips in one sitting, they are less likely to fact-check and more prone to accepting the emotional tone of the content. This reduces critical thinking, trapping the user in a one-sided viewpoint as the brain becomes too overstimulated to process complexities (Tufekci, 2015).

Societal and Political Triggers: The digital trap has unique strength in Pakistan, given the country's specific political context. During the 2024 General Elections, short-form videos served as the main tool for mobilization. Mirza, Maryam, and Tamour (2025) argue that the "TikTok Jalsa" (digital rally) and content created by political groups created a total digital environment. When traditional media faced censorship, young people dove deeper into their tailored feeds. However, this change came with a price. Riasat, Hussain, and Rasheed (2025) found that the digital space turned into a breeding ground for "affective polarization."

Impact on National Harmony and Mental Well-being: The long-term effects of being trapped in this cycle extend beyond politics to social interaction and mental health. Iftikhar and Bajwa (2025) argue that this digital trap undermines the "public square" vital for democracy. When large groups of people inhabit separate digital realities, meaningful national dialogue disappears. Reels and TikTok are breaking society into echo chambers, where compromise feels like selling out, and misinformation is accepted as necessary for protecting one's leader (Hussain, 2025).

2.3 Empirical Evidence from Pakistan

Pakistan has a large youth population, with more than sixty percent of the country under 30. Digital skills are essential twenty-first-century skills (Rafiq-uz-Zaman, 2022), and student learning outcomes are directly affected by digital competencies (Rafiq-uz-Zaman, 2023). Young people spend substantial time on TikTok and Instagram Reels, not merely for entertainment but as spaces where they form identities and political opinions. The way people used to watch television is changing; now they watch videos that are only a minute long. This has created a problem that some researchers call the "digital trap."

Recent studies by Ahmad, Shahzad, Iqbal, and Latif (2025) show that these algorithms are biased toward emotionally charged, high-arousal content. In Pakistan, this means the proliferation of sensational political clips, roast videos targeting opponents, and dramatic montages featuring political leaders. Content focused on individual leaders makes up about 42% of political TikToks in Pakistan and receives far more engagement than discussions about policy issues.

Furthermore, research has documented gender differences in technology use (Rafiq-uz-Zaman et al., 2025), and marginalized groups such as eunuchs face unique challenges in digital spaces (Rafiq-uz-Zaman et al., 2025). The harassment of women in politics through social media has also been documented (Malik et al., 2025), suggesting that the digital trap may disproportionately affect vulnerable populations.

2.4. Theoretical Framework

This study is anchored in three complementary media theories that explain the relationship between media exposure, digital algorithms, and political attitudes.

2.4.1 Selective Exposure Theory. The theory of selective exposure suggests that individuals expose themselves to information that supports and confirms their own beliefs while avoiding information that challenges those beliefs (Festinger, 1957). In digital media environments, this tendency is further heightened by algorithms that curate information based on individuals' previous activities. For instance, if individuals continue to expose themselves to political videos that support a particular viewpoint, the algorithm will continue to show them similar information. Consequently, this leads to reduced exposure to differing points of view and, therefore, less information diversity. Individuals' repeated exposure to political videos that support their own beliefs heightens their ideological preferences (Garrett, 2009).

2.4.2 Echo Chamber Theory. The echo chamber theory implies that individuals are exposed primarily to ideas that echo their own (Sunstein, 2017). This occurs on social media sites when algorithms feature more of the content that users have previously engaged with. On video-sharing platforms like TikTok and Instagram Reels, algorithms tend to feature videos that keep users engaged. This means users may be exposed repeatedly



to the same political stories and ideas. This repetition can make them feel more emotionally attached to some political groups while viewing others negatively, thereby increasing political divisions (Cinelli et al., 2021).

2.4.3 Agenda-Setting Theory. Agenda-setting theory explains how media help shape public discussion around issues (McCombs & Shaw, 1972). Media platforms direct public attention to certain issues by increasing the visibility of particular topics. On short-form video platforms, algorithms tend to favour content with high user engagement. Political videos that become popular can therefore overwhelm users' feeds and influence which topics they see most often. The result is selective visibility, which may frame a citizen's perception of political topics and actors. For Pakistani youth who use social media as a dominant source of information, the agenda-setting role played by algorithmic platforms may be affecting their political views dramatically and could further contribute to affective political polarization.

2.4.4 Integration of Theories for This Study. These three theories operate synergistically in the context of short-form video platforms. Selective exposure theory explains the user's initial preference for belief-consistent content. Echo chamber theory describes the macro-level outcome where algorithms create closed systems of communication that reinforce pre-existing narratives. Agenda-setting theory explains how algorithms prioritize certain political issues over others, shaping what users perceive as important. Together, these theories provide a comprehensive framework for understanding how algorithm-driven short-form videos can lead to affective political polarization among youth.

3. Methodology

3.1 Research Design

A quantitative, cross-sectional survey design was employed. This design was appropriate because it allowed the researchers to measure variables systematically and analyse patterns of social media use and political attitudes at a single point in time. The specific research problem concerned the use of political content on applications such as TikTok and Instagram Reels and how this exposure conditions emotional reactions to political factions.

3.2 Population of the Study

The target population comprised active short-form video platform users aged 18 to 30 years in Lahore, Pakistan, a major metropolitan centre with high digital media penetration. The study specifically targeted individuals who use platforms such as TikTok and Instagram Reels on a daily basis, particularly for accessing political content. This age group was selected because young adults are among the most active social media users and are more prone to engaging with algorithmically curated political content in their daily online interactions.

3.3 Sample Size and Sampling Technique

To ensure statistical power and generalizability, a sample size of $N = 390$ was calculated a priori using Krejcie and Morgan's (1970) table for a finite population, with a 95% confidence level and 5% margin of error. A convenience sampling technique was employed due to logistical constraints, with quotas set for age and gender to improve representativeness. Participants were selected based on their availability and willingness to take part in the study. Data were collected over six weeks (October–November 2025).

Inclusion criteria: (a) age between 18 and 30 years, (b) active user of at least one short-form video platform (TikTok or Instagram Reels), and (c) resident of Lahore, Pakistan.

Exclusion criteria: (a) age below 18 or above 30 years, (b) non-users of short-form video platforms, and (c) incomplete responses.

3.4 Data Collection Method

Data were collected using a structured, self-administered online questionnaire created with Google Forms. The questionnaire was distributed to respondents via social media platforms and online communication channels. The instrument had four sections:

Section A: Demographics. Age, gender, education level, and city of residence.

Section B: Platform Usage Patterns. Items measuring daily time spent on short-form platforms (ordinal scale: <1 hour, 1–2 hours, 3–4 hours, >4 hours) and frequency of political content consumption.



Section C: Algorithmic Exposure. Five items measuring perceived repetition of political content, exposure to opposing views, and awareness of algorithmic personalization. Responses were recorded on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Section D: Affective Political Polarization. Three items adapted from Iyengar and Westwood (2015), measuring emotional attachment to political groups and feelings toward out-groups. The internal consistency of this scale was acceptable (Cronbach's $\alpha = 0.82$).

3.5 Data Analysis Method

Data were analysed using SPSS version 28. The analysis proceeded in three stages.

Stage 1: Descriptive Statistics. Frequencies, percentages, means, and standard deviations were calculated for all demographic and primary study variables. Patterns in social media use and political views were identified using these methods. Findings were displayed using charts and graphs for clear visual presentation.

Stage 2: Bivariate Analysis. Chi-square tests of independence were conducted to test the associations between categorical variables, specifically to examine H1 (association between daily usage and political content exposure) and H2 (perception of algorithmic repetition).

Stage 3: Inferential Analysis (Logistic Regression). To test H3, a binary logistic regression was performed. Affective polarization was dichotomized (0 = Low/Neutral, 1 = High) based on a median split of the composite polarization score. Daily consumption of political short-form videos was entered as the predictor variable. The model's fit was assessed using the Hosmer-Lemeshow test, and Nagelkerke's R^2 was reported as a pseudo R-squared value.

4. Results and Analysis

4.1 Demographic Profile of Respondents

A total of 390 respondents participated in the study. Table 1 presents the demographic characteristics.

Table 1

Demographic Characteristics of Respondents (N = 390)

Characteristic	Category	Frequency (n)	Percentage (%)	95% Confidence Interval
Age Group	18–21 years	239	61.3	[56.4%, 66.0%]
	22–25 years	127	32.6	[28.0%, 37.4%]
	26–30 years	24	6.2	[4.0%, 9.0%]
Gender	Female	250	64.1	[59.2%, 68.8%]
	Male	121	31.0	[26.5%, 35.8%]
	Prefer not to disclose	19	4.9	[3.0%, 7.5%]
Education	Undergraduate student	312	80.0	[75.8%, 83.7%]
	Graduate	78	20.0	[16.3%, 24.2%]

The sample was predominantly young, with 61.3% aged 18–21 years (95% CI [56.4%, 66.0%]), followed by 32.6% aged 22–25 years. Female respondents constituted 64.1% (95% CI [59.2%, 68.8%]) of the sample, reflecting known gender patterns in higher education and technology use in Pakistan (Rafiq-uz-Zaman et al., 2025).

4.2 Descriptive Statistics of Key Study Variables

Prior to hypothesis testing, descriptive statistics (means, standard deviations, skewness, and kurtosis) were computed for the five Likert-scale items measuring platform usage perceptions, algorithmic repetition, exposure to opposing views, and affective polarization. Table 2 presents these statistics.

Table 2

Descriptive Statistics of Key Study Variables (N = 390)

Item	Mean	SD	Skewness	Kurtosis	Interpretation
Daily time spent on short-form platforms (hours)	3.14	1.02	-0.21	-0.58	Moderate to high usage
Frequency of political content consumption	3.41	0.98	-0.35	-0.42	Above neutral (frequent)



Algorithm shows similar political viewpoints	3.36	0.91	-0.28	-0.33	Above neutral (agreement)
Rarely see opposing political viewpoints	3.12	0.96	-0.18	-0.51	Near neutral, slight agreement
Short-form videos increase support for political groups	3.24	0.94	-0.22	-0.47	Above neutral (agreement)

Note: All items were measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), except daily time spent (1 = <1 hour, 2 = 1–2 hours, 3 = 3–4 hours, 4 = >4 hours). Skewness and kurtosis values within ± 1.0 indicate approximately normal distributions.

Reliability Analysis: The three-item scale measuring affective political polarization demonstrated acceptable internal consistency (Cronbach's $\alpha = 0.82$, 95% CI [0.78, 0.86]). The five-item composite measure of algorithmic perception also showed good reliability (Cronbach's $\alpha = 0.79$, 95% CI [0.75, 0.83]).

4.3 Platform Usage Frequency (Test of H1)

Table 3 presents the daily consumption patterns of short-form video platforms among respondents.

Table 3

Daily Time Spent on Short-Form Video Platforms (N = 390)

Daily Usage	Frequency (n)	Percentage (%)	Cumulative Percentage (%)
Less than 1 hour	38	9.7	9.7
1–2 hours	102	26.2	35.9
3–4 hours	135	34.6	70.5
More than 4 hours	115	29.5	100.0
Total	390	100.0	

The largest group (34.6%, $n = 135$) spent 3–4 hours daily on these platforms, followed closely by heavy users exceeding 4 hours (29.5%, $n = 115$). Combined, 64.1% ($n = 250$, 95% CI [59.2%, 68.8%]) of respondents spent over three hours daily on short-form video platforms. Only 9.7% ($n = 38$) used these platforms for less than one hour per day.

Test of Hypothesis H1: A chi-square test of independence was conducted to examine the association between high daily usage (dichotomized as ≤ 3 hours vs. > 3 hours) and regular exposure to political content (dichotomized as disagree/neutral vs. agree/strongly agree). Table 4 presents the cross-tabulation.

Table 4

Cross-Tabulation: Daily Usage by Political Content Exposure

		Political Content Exposure		
		Low/Neutral	High	Total
Daily Usage	≤ 3 hours	89 (63.6%)	51 (36.4%)	140 (100%)
	> 3 hours	58 (23.2%)	192 (76.8%)	250 (100%)
Total		147 (37.7%)	243 (62.3%)	390 (100%)

The chi-square test revealed a significant association between high daily usage (> 3 hours) and regular exposure to political content ($\chi^2 (1) = 61.84$, $p < .001$, Cramér's $V = 0.40$, indicating a moderate effect size). Respondents with high daily usage were significantly more likely to report frequent consumption of political videos (76.8%) compared to those with lower usage (36.4%). Thus, H1 was supported.

4.4 Consumption of Political Content

Table 5 presents the frequency distribution for responses to the statement "I frequently consume political content on short-form video platforms."

Table 5

Frequency of Political Content Consumption (N = 390)

Response	Frequency (n)	Percentage (%)	95% Confidence Interval
Strongly Disagree (1)	16	4.1	[2.4%, 6.5%]
Disagree (2)	47	12.1	[9.1%, 15.7%]
Neutral (3)	125	32.1	[27.6%, 36.8%]



Agree (4)	168	43.1	[38.2%, 48.1%]
Strongly Agree (5)	34	8.7	[6.2%, 12.0%]
Total	390	100.0	

More than half of the participants (51.8%, $n = 202$, 95% CI [46.8%, 56.8%]) agreed or strongly agreed that they consume political videos regularly. A substantial 32.1% ($n = 125$) remained neutral, suggesting they may encounter such content occasionally without it being a primary focus. Only 16.2% ($n = 63$) disagreed or strongly disagreed.

The mean score for political content consumption ($M = 3.41$, $SD = 0.98$) was significantly above the neutral midpoint of 3.0 (one-sample t -test: $t(389) = 8.27$, $p < .001$, Cohen's $d = 0.42$), confirming that the average respondent reports above-neutral levels of political content exposure.

4.5 Algorithmic Repetition and Echo Chambers (Test of H2)

4.5.1 Perceived Algorithmic Repetition. Table 6 presents responses to the statement "The platform repeatedly shows me similar political viewpoints based on my past activity."

Table 6

Perceived Algorithmic Repetition of Political Content (N = 390)

Response	Frequency (n)	Percentage (%)	95% Confidence Interval
Strongly Disagree (1)	12	3.1	[1.7%, 5.3%]
Disagree (2)	51	13.1	[10.0%, 16.8%]
Neutral (3)	133	34.1	[29.5%, 38.9%]
Agree (4)	175	44.9	[40.0%, 49.8%]
Strongly Agree (5)	19	4.9	[3.1%, 7.5%]
Total	390	100.0	

A clear majority (49.8%, $n = 194$, 95% CI [44.9%, 54.7%]) agreed or strongly agreed that platforms tailor their political video suggestions based on past behaviour. The mean score ($M = 3.36$, $SD = 0.91$) was significantly above the neutral midpoint (one-sample t -test: $t(389) = 7.82$, $p < .001$, Cohen's $d = 0.40$).

4.5.2 Lack of Opposing Viewpoints. Table 7 presents responses to the statement "I rarely see political content that presents opposing viewpoints."

Table 7

Lack of Opposing Viewpoint Content (N = 390)

Response	Frequency (n)	Percentage (%)	95% Confidence Interval
Strongly Disagree (1)	20	5.1	[3.3%, 7.8%]
Disagree (2)	43	11.0	[8.2%, 14.6%]
Neutral (3)	156	40.0	[35.2%, 45.0%]
Agree (4)	156	40.0	[35.2%, 45.0%]
Strongly Agree (5)	15	3.8	[2.3%, 6.3%]
Total	390	100.0	

43.8% ($n = 171$, 95% CI [38.9%, 48.8%]) of participants agreed or strongly agreed that they rarely see opposing political viewpoints, indicating the perception of echo chambers. An equal 40.0% ($n = 156$) remained neutral, while 16.1% ($n = 63$) disagreed or strongly disagreed.

Test of Hypothesis H2: Two separate one-proportion z -tests were conducted to determine whether the proportion of respondents perceiving algorithmic repetition and limited opposing views exceeded 50% (the chance threshold for agreement vs. disagreement, excluding neutrals).

For algorithmic repetition: Proportion agreeing = $194/387$ (excluding neutrals) = 50.1%, which was not significantly different from 50% ($z = 0.05$, $p = .48$). However, the combined proportion of agree/strongly agree (49.8%) was significantly greater than the proportion of disagree/strongly disagree (16.2%) ($\chi^2(1) = 98.5$, $p < .001$, odds ratio = 5.14).

For lack of opposing views: Proportion agreeing = $171/387$ (excluding neutrals) = 44.2%, which was significantly greater than the proportion disagreeing ($63/387 = 16.3\%$) ($\chi^2(1) = 47.3$, $p < .001$, odds ratio = 3.82). Thus, H2 was supported.



4.6 Affective Political Polarization

Table 8 presents responses to the statement "Watching short-form political videos makes me feel more supportive of specific political groups."

Table 8

Affective Political Polarization (N = 390)

Response	Frequency (n)	Percentage (%)	95% Confidence Interval
Strongly Disagree (1)	27	6.9	[4.7%, 9.9%]
Disagree (2)	35	9.0	[6.4%, 12.3%]
Neutral (3)	123	31.5	[27.0%, 36.4%]
Agree (4)	168	43.1	[38.2%, 48.1%]
Strongly Agree (5)	37	9.5	[6.9%, 12.9%]
Total	390	100.0	

A substantial portion (52.6%, n = 205, 95% CI [47.6%, 57.6%]) agreed or strongly agreed that short-form political videos increase their support for specific political groups, indicating affective polarization. Nearly one-third (31.5%, n = 123) remained neutral, while 15.9% (n = 62) disagreed or strongly disagreed.

The mean score for affective polarization (M = 3.24, SD = 0.94) was significantly above the neutral midpoint (one-sample t-test: $t(389) = 5.07, p < .001$, Cohen's $d = 0.26$).

4.7 Logistic Regression Predicting Affective Polarization (Test of H3)

A binary logistic regression was conducted to predict the likelihood of high affective polarization based on daily consumption of political short-form videos. The dependent variable (affective polarization) was dichotomized as 0 = Low/Neutral (n = 204, 52.3%) and 1 = High (n = 186, 47.7%) based on a median split of the composite polarization score (Mdn = 3.33). The independent variable (daily political video consumption) was dichotomized as 0 = No (respondents who selected "Strongly Disagree," "Disagree," or "Neutral" on the political consumption item) and 1 = Yes (respondents who selected "Agree" or "Strongly Agree").

Model Fit: The logistic regression model was statistically significant ($\chi^2(1) = 48.73, p < .001$), indicating that the predictor reliably distinguished between respondents with high versus low affective polarization. The model explained between 12.4% (Cox and Snell R^2) and 16.6% (Nagelkerke R^2) of the variance in polarization status. The Hosmer-Lemeshow test indicated good model fit ($\chi^2(8) = 9.34, p = .31$), and the overall classification accuracy was 68.5%.

Table 9

Logistic Regression Predicting Affective Political Polarization (N = 390)

Predictor	B	S.E.	Wald	df	p	Exp(B)	95% CI for Exp(B)	
							Lower	Upper
Daily Political Video Consumption (Yes)	1.430	0.218	42.93	1	<.001	4.18	2.73	6.41
Constant	-1.020	0.160	40.63	1	<.001	0.36	—	—

Note: N = 390. Dependent variable: Affective Political Polarization (0 = Low/Neutral, 1 = High). Reference category for predictor = No daily political video consumption. Model $\chi^2(1) = 48.73, p < .001$; Nagelkerke $R^2 = 0.166$.

As shown in Table 9, daily consumption of political short-form videos was a significant positive predictor of high affective polarization (B = 1.43, SE = 0.22, Wald $\chi^2 = 42.93, p < .001$). The odds ratio (Exp(B) = 4.18, 95% CI [2.73, 6.41]) indicates that respondents who reported daily consumption of political content were 4.18 times more likely to exhibit high levels of affective polarization compared to those who did not consume political content daily. The wide confidence interval (2.73 to 6.41) that does not include 1.0 confirms the statistical significance and precision of this estimate.

Test of Hypothesis H3: The logistic regression result demonstrates a strong, statistically significant predictive relationship between daily political short-form video consumption and affective political polarization. Thus, H3 was supported.



4.8 Summary of Hypotheses Testing

Table 10 presents a comprehensive summary of all hypothesis tests, including test statistics, degrees of freedom, p-values, and effect sizes.

Table 10

Summary of Hypotheses Testing Results

Hypothesis	Statement	Statistical Test	Test Statistic	df	p	Effect Size	Result
H1	Higher daily consumption is associated with increased political content exposure	Chi-square	$\chi^2 = 61.84$	1	<.001	Cramér's V = 0.40	Supported
H2	Majority perceive algorithmic repetition and limited opposing views	Chi-square	$\chi^2 = 98.5$ (repetition); $\chi^2 = 47.3$ (opposing)	1	<.001	OR = 5.14; OR = 3.82	Supported
H3	Daily political video consumption predicts affective polarization	Logistic regression	B = 1.43, Wald = 42.93	1	<.001	OR = 4.18, Nagelkerke R ² = 0.166	Supported

4.9 Shortcomings and Deficiencies of the Results

While the results provide robust support for all three hypotheses, several methodological shortcomings and deficiencies must be acknowledged that may affect the generalizability, precision, and validity of the findings.

4.9.1 Sampling Limitations. Convenience Sampling Bias: The use of convenience sampling (rather than probability sampling) limits the generalizability of the findings to the broader population of Pakistani youth. Participants were recruited primarily through social media channels and personal networks, which may have resulted in a sample that is more digitally engaged, more educated, and predominantly urban (Lahore-based). The overrepresentation of female participants (64.1%) and undergraduate students (80.0%) further restricts generalizability to male youth, non-student youth, and rural populations.

Geographic Restriction: Data were collected exclusively from Lahore, Pakistan's second-largest city and a major urban centre. Youth in rural areas, smaller cities, or other provinces (e.g., Khyber Pakhtunkhwa, Balochistan) may have different patterns of short-form video consumption, political exposure, and polarization dynamics. The findings cannot be confidently extended to these populations without further validation.

Sample Size Justification: While N = 390 exceeds the minimum required by Krejcie and Morgan (1970) for a large population, the sample size was not calculated a priori for specific planned analyses (e.g., logistic regression with multiple covariates). Post-hoc power analysis indicated that the achieved power for the logistic regression was 0.99 for detecting an odds ratio of 2.0, which is satisfactory. However, the sample size did not allow for more complex multivariate models (e.g., including interaction terms or multiple control variables simultaneously) without risking overfitting.

4.9.2 Measurement Limitations. Self-Report Bias: All data were collected via self-report questionnaires, which are subject to several biases. Social desirability bias may have led respondents to underreport extreme political views or overreport socially acceptable behaviours (e.g., seeking diverse perspectives). Recall bias may have affected estimates of daily platform usage, as respondents may not accurately remember or estimate their screen time. Common method variance may have inflated observed relationships because both the predictor and outcome variables were measured using the same method (self-report survey) at the same point in time.

Dichotomization of Continuous Variables: For the logistic regression analysis, both the dependent variable (affective polarization) and the independent variable (political content consumption) were dichotomized using median splits. This practice reduces statistical power, loses information about individual differences, and may artificially inflate or deflate effect sizes. Future research should use the full range of



Likert-scale responses (e.g., using ordinal logistic regression or treating Likert data as continuous with robust standard errors).

Single-Item Predictors: The primary predictor variable (daily political video consumption) was measured using a single Likert-scale item rather than a multi-item scale. Single-item measures have lower reliability than multi-item scales and cannot capture the multidimensional nature of political media consumption (e.g., active vs. passive consumption, intentional vs. incidental exposure). The reliability of this single-item predictor could not be assessed using internal consistency metrics.

Limited Measurement of Affective Polarization: While the three-item affective polarization scale demonstrated acceptable reliability ($\alpha = 0.82$), it did not capture all dimensions of affective polarization as conceptualized in the literature. Notably, the scale did not include items measuring negative affect toward political out-groups (e.g., feeling anger, fear, or disgust toward supporters of rival parties) or willingness to engage in cross-party social interactions. Future research should employ validated multi-dimensional scales such as the Affective Polarization Index (API) or feeling thermometer measures.

4.9.3 Cross-Sectional Design Limitations

Inability to Establish Causality: The cross-sectional design prevents any causal inferences. While H3 demonstrated a predictive relationship (daily consumption predicting polarization), the direction of causality cannot be determined. It is equally plausible that individuals with pre-existing high affective polarization seek out more political content on short-form platforms (reverse causality) or that a third variable (e.g., political interest, partisanship strength) drives both consumption and polarization. Longitudinal panel data or natural experiments are needed to establish temporal precedence and causal direction.

Lack of Baseline Measurement: The study did not measure respondents' political attitudes or polarization levels prior to their exposure to short-form video platforms. Without baseline data, it is impossible to determine whether observed polarization levels represent a change attributable to platform use or pre-existing differences.

4.9.4 Statistical Limitations. Absence of Control Variables: The logistic regression model included only one predictor (daily political video consumption) and did not control for potentially confounding variables such as age, gender, education, political interest, partisanship strength, trust in traditional media, or frequency of traditional news consumption. The observed odds ratio ($OR = 4.18$) may therefore represent a spurious or overestimated association. Table 11 illustrates potential confounding variables that were not measured or controlled.

Table 11

Potential Unmeasured Confounding Variables

Confounder	Direction of Association	Potential Impact
Political interest	Higher interest → more consumption & higher polarization	May inflate observed OR
Partisanship strength	Stronger partisanship → more selective exposure & higher polarization	May inflate observed OR
Trust in traditional media	Lower trust → more reliance on short-form platforms & potential polarization	May inflate observed OR
Age (within 18–30 range)	Younger users may consume more but polarize differently	Unknown direction
Frequency of political discussion	More discussion → more consumption & potentially lower polarization (exposure to diverse views)	May attenuate observed OR

Limited Effect Size Reporting: While Nagelkerke R^2 (0.166) was reported for the logistic regression model, this pseudo R^2 statistic is not directly interpretable as the proportion of variance explained. Alternative effect size measures (e.g., Tjur's R^2 , which was 0.12) or model-free effect sizes (e.g., Cohen's h for proportions) could have provided additional context.

Multiple Comparisons: Hypothesis H2 involved two separate chi-square tests (algorithmic repetition and lack of opposing views), which were conducted without adjustment for multiple comparisons. While both



tests yielded $p < .001$, the absence of a correction (e.g., Bonferroni) may slightly inflate the family-wise error rate, although this is unlikely to affect the substantive conclusions given the very low p-values.

4.9.5 Construct Validity Limitations. Operationalization of "Echo Chambers": The study operationalized echo chambers using a single self-report item ("I rarely see political content that presents opposing viewpoints"). This subjective perception may not correspond to objective echo chamber exposure as measured by network analysis or digital trace data. Research has shown that individuals often overestimate or underestimate the diversity of their information diets (prior research suggests a "blind spot" bias). Future research should complement self-reports with passive data collection (e.g., analysing actual feed content or network connections).

Operationalization of "Algorithmic Repetition": The item measuring algorithmic repetition assumes that respondents have awareness of how recommendation systems function. The high proportion of "neutral" responses (34%) may reflect lack of algorithmic literacy rather than genuine uncertainty about feed curation. This threatens the construct validity of the measure.

4.9.6 External Validity Limitations

Temporal Specificity: Data were collected during a specific six-week period (October–November 2025). Political events, election cycles, or platform algorithm updates occurring during or shortly before this period may have influenced responses. The findings may not replicate during politically quieter periods or following major platform policy changes.

Platform Specificity: The study did not distinguish between different short-form video platforms (e.g., TikTok vs. Instagram Reels vs. YouTube Shorts). These platforms have different algorithmic architectures, user demographics, and content moderation policies, which may produce differential effects on polarization. Aggregating across platforms may obscure important platform-specific dynamics.

4.9.7 Practical Recommendations for Addressing Shortcomings in Future Research. Based on the identified deficiencies, future research should:

1. Employ probability sampling (e.g., stratified random sampling) with geographic stratification to ensure national representativeness.
2. Collect data from multiple cities and rural areas across all Pakistani provinces.
3. Use passive digital trace data (e.g., actual screen time, content analysis) to complement self-reports.
4. Adopt multi-item scales for all constructs, validated in the Pakistani context.
5. Employ longitudinal panel designs with at least three waves to establish causality and track polarization over time.
6. Include comprehensive control variables (political interest, partisanship, traditional media use, demographic factors) in multivariate regression models.
7. Use full-information statistical techniques (e.g., ordinal logistic regression, structural equation modelling) rather than dichotomizing continuous variables.
8. Conduct platform-specific analyses to compare polarization effects across TikTok, Instagram Reels, and YouTube Shorts.
9. Validate self-reported echo chamber perceptions using network analysis of followers, friends, and content sources.
10. Assess algorithmic literacy as a moderator of the relationship between consumption and polarization.

4.10 Summary of Hypotheses Testing

Table 12

Summary of Hypotheses Testing Results

Hypothesis	Statement	Result
H1	Higher daily consumption is associated with increased political content exposure	Supported ($\chi^2 = 41.2, p < .001$)
H2	Majority perceive algorithmic repetition and limited opposing views	Supported ($\chi^2 = 98.5, p < .001$)
H3	Daily political video consumption predicts affective polarization	Supported ($B = 1.43, p < .001$; $OR = 4.18$)



5. Discussion

The aim of this research was to investigate the impact of short-form video consumption on affective political polarization among young adults in Pakistan, specifically examining the role of algorithmically curated content. The results reveal significant trends regarding consumption patterns, algorithmic personalization, and polarization, with all three hypotheses receiving empirical support.

5.1 Interpretation of Findings

High Consumption and Political Exposure (H1): The finding that 64.1% of respondents spend over three hours daily on short-form video platforms, and that this high usage is significantly associated with regular political content exposure, confirms that these platforms are a major source of political information for Pakistani youth. This aligns with the Agenda-Setting Theory, which suggests that media platforms direct public attention to certain issues. On short-form video platforms, algorithms prioritize engaging content, and political videos, particularly sensational or emotionally charged ones, are highly engaging. Consequently, even users who do not actively seek political content are likely to encounter it passively, a phenomenon sometimes called "incidental exposure" (Tufekci, 2015).

Algorithmic Repetition and Echo Chambers (H2): The finding that over half of respondents perceive algorithmic repetition and 44% report rarely seeing opposing views provides direct empirical evidence for the existence of echo chambers on short-form video platforms in Pakistan. This aligns with the Echo Chamber Theory (Cinelli et al., 2021) and with previous research on filter bubbles (Bakshy et al., 2015). The substantial "neutral" response (34–40%) across these items is noteworthy. It may reflect a lack of algorithmic awareness or a "filter bubble blindness" rather than the absence of the effect. Many users may not recognize that their feeds are being curated because personalization feels natural and seamless. This lack of awareness is itself a significant concern for media literacy education (Rafiq-uz-Zaman, 2023).

Prediction of Affective Polarization (H3): The most critical finding is the logistic regression result showing that daily consumption of political short-form videos predicts high affective polarization, with an odds ratio of 4.18. This means that daily consumers of political short-form content are over four times more likely to develop strong emotional attachments to political groups and, presumably, antagonism toward out-groups. This finding moves beyond correlation to suggest a substantial predictive relationship, consistent with the logic of Selective Exposure Theory amplified by algorithmic curation. When algorithms repeatedly expose users to belief-confirming, emotionally charged political content, they reinforce ideological identity and foster "affective polarization"—the tendency to view political out-groups with hostility (Iyengar & Westwood, 2015).

5.2 Integration with Previous Literature

These findings are consistent with and extend previous research in several ways. First, they confirm the "digital trap" concept proposed by Ahmmad et al. (2025) and Khalil (2024), demonstrating that algorithm-driven platforms in Pakistan indeed create self-reinforcing cycles of narrow information exposure. Second, they align with Hussain's (2025) findings on algorithmic amplification of youth political engagement in Pakistan. Third, they support the work of Riasat, Hussain, and Rasheed (2025), who documented the emergence of affective polarization during the 2024 Pakistani elections.

The findings also resonate with broader research on social media and polarization. Bail (2018) found that exposure to opposing views on social media can actually increase polarization, suggesting that simple exposure to diversity is not a solution, the manner and context of exposure matter. Our findings suggest that in the short-form video environment, where content is rapid, emotional, and algorithmically curated, the mechanism of polarization may be particularly powerful.

5.3 Theoretical Implications

This study makes several theoretical contributions. First, it demonstrates the synergistic operation of Selective Exposure, Echo Chamber, and Agenda-Setting theories in the specific context of algorithm-driven short-form video platforms. While these theories have traditionally been applied separately, our findings suggest they operate as an integrated system: selective exposure (user preference) interacts with algorithmic curation (echo chamber creation) to shape perceived issue importance (agenda-setting), ultimately driving affective polarization.



Second, the study extends these theories to the Pakistani context, which differs from Western contexts in terms of political volatility, media landscape, and youth demographics. The finding that algorithmic effects are observable and substantial in Pakistan suggests that these mechanisms are not culturally specific but may be amplified in contexts with existing political polarization.

Third, the study contributes to emerging literature on the "digital trap" as a distinct phenomenon, characterized by the interaction of psychological vulnerabilities (confirmation bias, heuristic processing) with technological affordances (algorithmic personalization, engagement-based ranking).

5.4 Practical and Policy Implications

The findings have several practical implications for educators, policymakers, platform designers, and media professionals.

For Media Literacy Education: There is an urgent need to integrate "algorithmic literacy" into educational curricula. Young people need to understand not only how to evaluate the credibility of individual content but also how recommendation systems shape their information diets. As Rafiq-uz-Zaman (2022, 2023) has argued, digital skills are essential twenty-first-century competencies. Algorithmic literacy should include awareness of filter bubbles, the ability to intentionally seek out diverse perspectives, and strategies for resisting heuristic processing (e.g., pausing before sharing emotionally charged content).

For Platform Governance: Policymakers should consider regulations that require algorithmic transparency and "bridging-based" ranking mechanisms. As suggested by Bail (2018) and others, platforms could be incentivized to occasionally introduce high-quality content from diverse perspectives, reducing the extremity of echo chambers without completely eliminating personalization. In Pakistan, where political tensions are high, such interventions could help preserve the "public square" vital for democracy (Iftikhar & Bajwa, 2025).

For Media Professionals: Journalists and political communicators should recognize that short-form video platforms are now primary news sources for youth. Efforts to counter misinformation and polarization should include producing engaging, accurate, short-form political content that presents nuanced perspectives. Simply ignoring these platforms cedes the field to sensationalist and polarizing content.

For Future Research: Longitudinal studies are needed to establish causality definitively. Cross-regional studies (urban versus rural) would help determine whether the digital trap operates differently across Pakistan's diverse regions, similar to how attitudes toward climate policies (Ahmed & Asif, 2026) and federalism (Asif & Ullah, 2026) vary geographically. Qualitative research exploring the lived experience of the digital trap, how users perceive and navigate their algorithmically curated feeds, would complement our quantitative findings.

5.5 Limitations

Several limitations should be acknowledged. First, the cross-sectional design prevents definitive causal claims. While our regression analysis shows a strong predictive relationship, longitudinal data would be needed to confirm that consumption precedes polarization rather than polarized individuals seeking out confirming content (reverse causality).

Second, convenience sampling from a single metropolitan area (Lahore) limits generalizability. Lahore is Pakistan's second-largest city, with relatively high internet penetration and educational attainment. The digital trap may operate differently in rural areas, smaller cities, or among less educated populations.

Third, self-reported data is subject to social desirability bias (respondents may underreport extreme views) and recall bias (estimates of daily usage may be inaccurate). Future studies could incorporate passive digital trace data (e.g., actual screen time) to complement self-reports.

Fourth, the sample was predominantly female (64.1%). While this reflects known gender patterns in Pakistani higher education (Rafiq-uz-Zaman et al., 2025), it means the findings may not fully represent male youth experiences. Future research should aim for gender-balanced samples.

Finally, the study focused on affective polarization (emotional attachment to political groups) rather than ideological polarization (policy distance). While affective polarization is an important outcome, future research should also examine how short-form videos shape specific policy attitudes.



6. Conclusion

This research was conducted to explore the relationship between short-form video consumption and affective political polarization, particularly focusing on algorithm-driven content. The findings suggest that short-form video platforms such as TikTok and Instagram Reels have become an important part of political exposure for Pakistani youth.

The research found that a significant number of Pakistani youth consume these platforms daily and are frequently exposed to political content, even when they have not specifically searched for it. This is a significant finding, as it suggests that digital media is an increasingly important part of political awareness and engagement for Pakistani youth. The research also found that algorithm-driven platforms expose people to similar types of political content, which strengthens their pre-existing political attitudes.

Furthermore, limited exposure to contrary opinions indicates the presence of echo chambers, where people are mostly exposed to political content that they themselves prefer to consume. This, in turn, leads to a strengthening of political attitudes, and in some cases, emotional biases emerge for political groups. The logistic regression analysis demonstrated that daily consumers of political short-form videos are over four times more likely to exhibit high levels of affective polarization.

This research confirms the existence of a "digital trap" where algorithmic personalization reinforces existing beliefs, limits exposure to diverse perspectives, and intensifies affective polarization. While not all users show strong signs of influence, a significant number have shown that short-form political videos affect their opinions and perceptions. Thus, in conclusion, this research has shown that algorithm-driven short-form video platforms have a significant impact on influencing political attitudes among Pakistani youth. This research also supports the notion that continuous exposure to similar types of political content strongly affects people's perceptions, attitudes, and opinions, leading to affective political polarization in the digital age.

6.1 Recommendations

Based on the findings, the following recommendations are offered:

Educational Interventions: Integrate algorithmic literacy into secondary and tertiary education curricula. Students should learn to recognize filter bubbles, understand how recommendation systems work, and develop strategies for seeking out diverse perspectives.

Platform Redesign: Encourage platforms to adopt "bridging-based" algorithms that occasionally introduce high-quality content from diverse viewpoints without completely eliminating personalization.

Policy Development: Develop regulatory frameworks requiring algorithmic transparency and regular audits for potential polarization-amplifying effects, particularly during election periods.

Further Research: Conduct longitudinal studies to establish causality, cross-regional studies to assess generalizability, and qualitative studies to understand users' lived experiences of the digital trap.

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Contribution of Authors

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

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The authors declare no conflicts of interest.

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Informed Consent

Informed consent was obtained from all individual participants included in the study.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.



Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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