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Political Memes as Digital Political Communication: A Structural Equation Model of Exposure, Engagement, Perceived Influence, and Political Perception Among College Youth

[1]Mr. A. Infant Kingsley, [2]Dr. G. Arul Selvi

Research Scholar, Department of Visual Communication, Holy Cross College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli, Tamilnadu, India.

Assistant Professor, Department of Visual Communication, Holy Cross College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli, Tamilnadu, India.

Abstract

Political memes have become a pervasive vehicle of informal political communication among youth on social media, yet the psychometric and structural relationships among exposure, engagement, perceived influence, political perception, and critical media literacy remain under-specified in the empirical literature. This paper reports a complete, reproducible statistical pipeline descriptive analysis, reliability analysis, normality testing, correlation analysis, multiple-comparison-corrected group tests, multiple regression, and structural equation modeling (SEM) applied to a 360-record, 30-item Likert questionnaire organized around five theorized constructs: Political Meme Exposure, Meme Engagement, Perceived Influence, Political Perception, and Critical/Media Literacy. the study is presented as a methodological and instrument-validation exercise empirical finding about real students. Reliability coefficients for the five subscales ranged from acceptable to good (Cronbach's alpha = 0.67–0.82). A five-factor measurement model combined with a hypothesized structural model (Exposure → Engagement → Influence → Perception, with direct Exposure → Perception and Literacy → Perception paths) achieved a good fit to the pilot data (CFI = .973, TLI = .971, RMSEA = .021), and Exposure showed the strongest standardized structural effect on Perception ($\beta = .52$, $p < .001$), followed by Influence ($\beta = .31$, $p < .001$). We describe in full the stratified-sampling framework, pre-processing rules, and analytic code needed to reproduce every statistic and figure, so that the pipeline can be applied unchanged to genuine field data once collected. Implications for questionnaire refinement, sampling strategy, and future confirmatory research on meme-mediated political socialization are discussed.

Keywords: political memes; digital political communication; structural equation modeling; media literacy; youth political socialization; stratified sampling; instrument validation

. Introduction

Social media has reconfigured the informal channels through which young citizens encounter political content, and among the most visible of these channels is the political meme: a compact, often humorous, image-text unit that circulates rapidly across platforms (Shifman, 2013). Unlike traditional political messaging, memes are frequently encountered incidentally, while users are engaged in unrelated social or entertainment activity, which places them squarely within the broader literature on incidental exposure to political information (Tewksbury, Weaver, & Maddex, 2001; Weeks, Lane, Kim, Lee, & Kwak, 2017). Because incidental, meme-based exposure does not require active political interest, it may reach segments of the youth population who would otherwise avoid political content altogether, raising both an opportunity (broadened informal civic engagement) and a risk (uncritical or emotionally driven uptake of politically loaded content).

The everyday, vernacular character of memes their humor, satire, and shareability allows them to function simultaneously as entertainment and as informal political communication (Highfield, 2016a, 2016b). This dual character complicates any simple exposure-to-attitude model: a student may be highly exposed to political memes

without engaging critically with their content, or may engage playfully (liking, sharing, discussing) without necessarily updating any political perception. Distinguishing exposure from engagement, and both from perceived influence and actual reported changes in political perception, therefore requires a measurement strategy capable of separating correlated but conceptually distinct latent constructs a task for which structural equation modeling (SEM) is well suited (Kline, 2016).

A further complication is that individuals differ in their capacity to process meme-based political content critically. Critical or media literacy the disposition to check sources, compare claims against reliable information, and distinguish satire from factual assertion has been shown in adjacent literatures to condition how media-literacy interventions and misinformation corrections are received (Vraga & Tully, 2019). It is plausible, though not yet well established empirically for the specific case of political memes, that critical literacy dampens the translation of meme exposure and influence into shifts in political perception, functioning as a protective or moderating cognitive resource.

Saravanan and John (2025), in their study titled "The Impact of Digital Literacy on Financial Behaviour and Financial Self-Confidence in Generation Z," examined the relationship between digital literacy, financial behaviour, and financial self-confidence among Generation Z. The study provides a relevant foundation for understanding the importance of digital competencies in shaping individual responses to information in technology-mediated environments. In the context of political communication, this perspective suggests that digital literacy may be an important consideration when examining how college youth encounter, interpret, and respond to political memes and other visual messages circulated through social media. However, the relationship between digital literacy and political perception requires specific empirical investigation

This paper addresses three practical and methodological aims. First, it specifies and documents in full a 30-item, five-construct questionnaire (Political Meme Exposure, Meme Engagement, Perceived Influence, Political Perception, and Critical/Media Literacy) suitable for studying meme-mediated political socialization among college youth, along with a stratified sampling design intended to support population-level inference across residence (rural/urban) and academic level (undergraduate/postgraduate) strata. Second, it demonstrates a complete, reproducible statistical analysis pipeline spanning descriptive statistics, reliability analysis, correlation analysis, multiple-comparison-corrected group testing, multiple regression, and SEM with an accompanying path diagram coded in Python and openly described so that it can be re-run without modification. Third, and most importantly for readers evaluating this manuscript,

The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature on political memes, incidental political exposure, and media literacy, and states the hypothesized structural model. Section 3 details the questionnaire, stratified sampling framework, pre-processing rules, and full analytic plan. Section 4 reports descriptive, reliability, correlational, group-comparison, regression, and SEM results from the pilot dataset. Section 5 discusses the substantive and methodological implications, and Section 6 addresses limitations, generalizability, and directions for a confirmatory field study.

2. Literature Review and Hypothesized Model

2.1 Political Memes as Informal Political Communication

Shifman (2013) defines internet memes as digital content units created with awareness of one another and circulated, imitated, and transformed by many users; political memes apply this logic to political actors, events, and issues, typically through humor or satire. Highfield (2016a) documents how such vernacular practices image macros, parody accounts, hashtag play have become embedded in everyday political talk on social media, blurring the boundary between entertainment and civic expression (Highfield, 2016b). Because memes are short, visually driven, and often shared within social rather than explicitly political contexts, they are well positioned to reach politically inattentive audiences who would not seek out political news directly.

2.2 Incidental Exposure and Engagement

The concept of incidental exposure captures the idea that political information is often encountered as a byproduct of otherwise non-political online activity (Tewksbury et al., 2001). Weeks et al. (2017) show that patterns of incidental and selective exposure jointly shape subsequent political information sharing, suggesting that exposure alone is analytically distinct from what a person subsequently does with that exposure that is, from engagement (reading carefully, reacting, sharing, discussing, or seeking further information). This distinction motivates treating Political Meme Exposure and Meme Engagement as separate, correlated latent constructs in the present measurement model rather than collapsing them into a single index

Saravanan and John (2026), in their article "Digital Literacy as a Mediator between Financial Engineering Innovations and Financial Behaviour among Gen Z," examined digital literacy within a mediating framework connecting financial engineering innovations and financial behaviour. The study is relevant to the broader discussion of digital literacy and mediated behavioural relationships. In the present research context, this provides a conceptual basis for considering whether individual competencies and interpretive processes may help explain differences in responses to digitally circulated political messages. However, the proposed relationships involving political meme exposure, engagement, perceived influence, and political perception must be established through political communication theory and evidence specific to the study population.

2.3 Perceived Influence and Political Perception

A further conceptual distinction separates a respondent's general belief that memes can influence political views (perceived influence, a relatively abstract, third-person-style judgment) from a respondent's report that memes have influenced their own political perception (a first-person, self-referential judgment). Prior work on humor and political communication suggests both pathways may operate together: general beliefs about meme influence may prime or license the acknowledgment of one's own susceptibility, while direct exposure may independently shape self-reported perception through repeated, low-effort processing. The hypothesized structural model therefore allows Exposure to affect Perception both indirectly (through Engagement and Influence) and directly, alongside an Influence-to-Perception path.

Saravanan and John (2026), in their research titled "Does AI Build Financial Confidence? A Structural Equation Model of AI Usage, Financial Self-Efficacy, and Financial Behaviour among Generation Z," investigated technology usage and behavioural relationships using structural equation modelling. The study is methodologically relevant to the present research because SEM enables researchers to examine interconnected relationships among constructs within a unified analytical framework. Similarly, the relationship between political meme exposure, online engagement, perceived influence, and political perception can be examined through an SEM framework. Nevertheless, the behavioural relationships identified in the financial context should not automatically be generalised to political communication.

2.4 Critical / Media Literacy as a Parallel Cognitive Resource

Research on news media literacy interventions indicates that the disposition to evaluate sources and cross-check claims can shape how corrective or persuasive political content is processed (Vraga & Tully, 2019). We treat Critical/Media Literacy as a fifth latent construct, specified with a direct structural path to Political Perception and an exogenous covariance with Exposure, reflecting the possibility that more critically literate students are differentially exposed to (or differentially attentive to) political meme content, without assuming a specific causal direction for that covariance.

2.5 Hypothesized Structural Model

Based on the foregoing, the measurement model specifies five latent constructs, each indicated by its corresponding Likert items (PME1–PME6 for Exposure; ENG1–ENG5 for Engagement; INF1–INF6 for Influence; PER1–PER8 for Perception; LIT1–LIT5 for Literacy). The structural model specifies: (H1) Exposure → Engagement; (H2) Exposure

→ Influence; (H3) Engagement → Influence; (H4) Influence → Perception; (H5) Exposure → Perception (direct); (H6) Literacy → Perception (direct); and an exogenous covariance between Exposure and Literacy. This structure treats Perception as the ultimate endogenous outcome of a communication chain that begins with incidental exposure and is channeled through engagement and perceived influence, while allowing literacy to operate as an independent, parallel predictor.

3. Methods

3.1 Research Context and Data Status

The pilot dataset analyzed here (N = 360) was constructed to trial a 30-item questionnaire having genuine sample of college students. As stated in the transparency box above, all 360 records are synthetic and were not collected from real respondents. The sampling design, questionnaire, and analytic pipeline described below are nonetheless presented at full field-study specification.

3.2 Instrument

The questionnaire comprises 30 five-point Likert items (1 = Strongly Disagree to 5 = Strongly Agree) organized into five constructs, plus a demographic and media-use block. Table 1 summarizes the constructs and their indicators.

Construct	Item Codes	n items	Example item
Political Meme Exposure (PME)	PME1–PME6	6	"I frequently see political memes while using social media."
Meme Engagement (ENG)	ENG1–ENG5	5	"I share or forward political memes with others."
Perceived Influence (INF)	INF1–INF6	6	"Political memes can influence how young people view political issues."
Political Perception (PER)	PER1–PER8	8	"Political memes influence how I perceive current political issues."
Critical/Media Literacy (LIT)	LIT1–LIT5	5	"I usually check the source before believing a political meme."

Table 1. Questionnaire constructs, item codes, and example

Demographic and contextual variables include Residence (Rural/Urban), Gender (Male/Female), Level (UG/PG), Year of Study, Discipline (Arts/Humanities, Commerce/Management, Science/Technology), College_Code, District, Age (years), Daily Social Media Use (categorical, <1 hour to >4 hours), Primary Platform, and self-reported Political Meme Exposure Frequency (Rarely to Very Often). These variables serve both as stratification/screening variables and as grouping variables for the inferential analyses reported in Section 4.

3.3 Data Assumptions, Variable Types, and Pre-processing

All 30 Likert items are treated as ordinal indicators with an assumed underlying continuous latent response, a standard assumption for maximum-likelihood SEM and for construct-mean composites in this literature; expected range for every item is the closed interval [1, 5]. Age is treated as a continuous numeric variable (expected plausible range 17–

30 years for a UG/PG college sample). Residence, Gender, Level, Discipline, College_Code, District, Daily_Social_Media_Use, Primary_Platform, and Political_Meme_Exposure_Frequency are treated as unordered or ordered categorical variables as appropriate.

Pre-processing rules, applied identically to pilot and (future) field data: (i) records with any missing value on a core Likert item are flagged and, if missingness exceeds 20% of items within a construct, the respondent is excluded; construct means are otherwise computed on available items. In the present pilot data, no missing values were present on any Likert item or on Age. (ii) Likert responses outside the valid 1–5 range are treated as data-entry errors and set to missing; none were found in the pilot data. (iii) Age outliers are flagged using the 1.5× interquartile-range (IQR) rule; none were flagged in the pilot data (range 18–26 years, M = 20.86, SD = 1.94). (iv) Because Likert-item outliers are not meaningful in the conventional sense (values are bounded and ordinal), no case-deletion outlier rule is applied to item-level data beyond the range check; instead, robustness to non-normality is addressed at the estimation stage (Section 3.5).

Saravanan & G John (2026), in the study "The Influence of Digital Financial Literacy on Electronic Financial Behaviour: Mediating Role of Financial Self-Efficacy and Comparison between STEM and Non-STEM Students," addressed the role of self-efficacy as a mediating mechanism in the relationship between digital financial literacy and electronic financial behaviour. This research offers a useful conceptual reference for investigating the mechanisms through which digital experiences may be associated with individual outcomes. Applied cautiously to political communication, the study supports considering not only exposure to digital content but also the processes through which users interpret and respond to that content. In particular, political meme engagement and perceived influence warrant examination as distinct constructs rather than being treated as interchangeable measures.

Distributional assumptions: normality of construct-mean composites was evaluated using the Shapiro–Wilk test. Several constructs mean departed significantly from normality at $\alpha = .05$ (Political Perception, $W = .984$, $p = .0005$; Critical/Media Literacy, $W = .987$, $p = .002$; Meme Engagement, $W = .990$, $p = .015$; Perceived Influence, $W = .991$, $p = .033$), while Political Meme Exposure approximated normality ($W = .992$, $p = .059$). Because Likert-scale composites of this kind are frequently mildly non-normal at moderate sample sizes without materially biasing parameter estimates, and because maximum-likelihood SEM is reasonably robust to mild non-normality at $N = 360$, no transformation was applied; instead, robustness was cross-checked via non-parametric (Spearman) correlations alongside Pearson correlations, and Welch's t-test (which does not assume equal variances) was used for all group comparisons.

3.4 Sampling Framework

Simple random sampling from a single unstratified list of eligible students risks both inefficiency and bias when a population is known, a priori, to vary systematically along theoretically relevant lines here, residence (rural vs. urban) and academic level (undergraduate vs. postgraduate), both of which plausibly relate to daily social-media access, platform choice, and exposure to political content. A stratified random sampling design is therefore recommended and was used to structure the pilot allocation: strata are defined by the cross-classification of Residence (Rural, Urban) and Level (UG, PG), yielding four strata. Within each stratum, respondents are to be drawn at random from the eligible sampling frame (e.g., enrollment records of participating colleges), with allocation proportional to each stratum's known or estimated share of the target population (proportional allocation) unless a specific stratum is of particular substantive interest, in which case modest oversampling of that stratum (disproportionate allocation) with subsequent analytic weighting is recommended.

The pilot dataset's realized allocation (Table 2) illustrates an unequal, realistic allocation rather than an artificially balanced 25/25/25/25 split, consistent with plausible population proportions in a mixed rural–urban college network.

Residence	Level	n	% of total (N = 360)
Rural	UG	101	28.1%
Rural	PG	65	18.1%
Urban	UG	120	33.3%
Urban	PG	74	20.6%

Table 2. Stratified allocation by Residence × Level.

Implications for inference and potential biases: proportional stratified sampling guarantees representation of each Residence × Level combination and typically reduces the standard error of population estimates relative to simple random sampling whenever the strata differ in their construct means, because between-stratum variance is removed from the sampling-error term. However, three biases must be monitored in a field application. First, if the sampling frame (institutional enrollment lists) systematically under- or over-represents certain colleges, districts, or disciplines, stratified sampling by Residence and Level alone will not correct for that frame bias. Second, non-response bias may operate differentially across strata (e.g., rural students with lower connectivity may be harder to reach for an online questionnaire), which would bias stratum-specific means even with correct allocation; a minimum response-rate target and non-response follow-up by stratum is recommended. Third, self-selection into the primary social-media platform (e.g., WhatsApp vs. Instagram vs. X) is not itself stratified in this design and should be treated as a measured covariate rather than a sampling stratum, since platform choice is plausibly endogenous to the outcomes under study.

3.5 Statistical Analysis Plan

Descriptive statistics. For each construct-mean composite: N, mean, median, standard deviation, interquartile range, minimum, maximum, skewness, and kurtosis. For categorical demographic variables: frequencies and percentages.

Reliability. Internal consistency of each five-to-eight-item subscale was assessed with Cronbach's alpha, with $\alpha \geq .70$ treated as the conventional acceptability threshold (Nunnally & Bernstein, 1994), while noting that alphas in the .65–.70 range are common and often tolerated for shorter subscales (5 items) in early-stage instrument validation.

Normality. Shapiro–Wilk tests on construct-mean composites, reported alongside skewness/kurtosis, to inform the choice between parametric and rank-based inferential tests.

Correlation. Pearson product-moment correlations among the five construct means, cross-checked with Spearman rank correlations given the non-normality noted above.

Group comparisons. Welch's independent-samples t-tests (unequal variances) for two-level grouping variables (Gender: Male/Female; Residence: Rural/Urban; Level: UG/PG) on each construct mean, with Cohen's d effect sizes; one-way ANOVA with eta-squared for the three-level Discipline variable. Because this yields 20 simultaneous significance tests across the five constructs and four grouping variables, both a Bonferroni-corrected family-wise alpha (.05 / 20 = .0025) and the Benjamini–Hochberg false discovery rate (FDR) procedure are reported, with FDR treated as the primary decision rule given its better power-versus-Type-I-error balance in exploratory multi-construct designs, and Bonferroni reported as the more conservative benchmark.

Multiple regression. An ordinary least squares regression of Political Perception (construct mean) on Political Meme Exposure, Meme Engagement, Perceived Influence, and Critical/Media Literacy (construct means) was estimated as

a construct-level (manifest-variable) complement to the latent-variable SEM, reported with unstandardized coefficients, standard errors, t-values, p-values, and 95% confidence intervals.

Structural equation modeling. A two-step SEM approach (Anderson & Gerbing, 1988) was used: the measurement model (five-factor confirmatory factor structure) was specified jointly with the structural model (Section 2.5) and estimated in a single step using maximum-likelihood estimation (semopy's MLW objective, mathematically equivalent to standard ML for complete continuous/ordinal-as-continuous data) given the absence of missing data. Model fit was evaluated using the chi-square test and its p-value (reported but not used as a sole arbiter of fit, given its known sensitivity to sample size), the Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI), with values ≥ .95 treated as indicating good fit and ≥ .90 as acceptable fit, and the Root Mean Square Error of Approximation (RMSEA), with values ≤ .06 treated as good fit and ≤ .08 as acceptable fit, following the widely used (if debated) benchmarks summarized by Hu and Bentler (1999). AIC and BIC are reported for potential model comparison in future confirmatory work. A path diagram displaying standardized loadings and structural coefficients was generated directly from the fitted model object.

Multiple-testing corrections were applied specifically to the 20 group-comparison tests and the five ANOVA tests (25 tests total for demographic contrasts); the regression and SEM analyses are each single, pre-specified confirmatory models and are not subjected to a separate multiplicity correction, consistent with standard practice for a single hypothesized structural model.

3.6 Software and Reproducibility

All analyses were conducted in Python 3.12 using pandas and NumPy for data handling, SciPy and statsmodels for descriptive and inferential statistics (including Benjamini–Hochberg correction via statsmodels.stats.multitest), semopy 2.3 for structural equation modeling and path-diagram generation, and Matplotlib/Seaborn for the correlation heatmap, distribution plots, and stratified comparison charts. The complete analysis code, organized as a reproducible project (data/, scripts/, outputs/tables/, outputs/figures/), is provided as supplementary material accompanying this manuscript; the Appendix reproduces the core code in full.

4. Results

All results below are computed on the N = 360 dataset and are reported to demonstrate the analytic pipeline; they should not be read as substantive findings about real students (see Transparency and Data-Status Statement).

4.1 Sample Composition

The pilot sample comprised 360 records: 194 (53.9%) coded Urban and 166 (46.1%) Rural residence; 189 (52.5%) coded Female and 171 (47.5%) Male; 221 (61.4%) at the undergraduate (UG) level and 139 (38.6%) at the postgraduate (PG) level; and discipline distributed across Arts/Humanities, Commerce/Management, and Science/Technology categories (intentionally unequal, not forced to equal thirds). Age ranged from 18 to 26 years (M = 20.86, SD = 1.94), with no cases flagged by the IQR outlier rule.

4.2 Descriptive Statistics and Reliability

Table 3 reports descriptive statistics for the five construct-mean composites. All five means cluster near the scale midpoint (3.05–3.21 on the 1–5 range), consistent with the deliberately non-extreme response generation used in constructing the pilot data.

Construct	N	Mean	Median	SD	IQR	Min	Max	Skew	Kurtosis	Cronbach's α
Political Meme Exposure	360	3.108	3.00	0.686	1.00	1.17	5.00	0.091	-0.149	0.761
Meme Engagement	360	3.108	3.20	0.727	1.00	1.00	5.00	-0.055	-0.286	0.720
Perceived Influence	360	3.046	3.00	0.711	1.00	1.00	4.83	-0.079	-0.436	0.762
Political Perception	360	3.139	3.12	0.733	1.13	1.50	4.88	0.101	-0.733	0.820
Critical/Media Literacy	360	3.207	3.20	0.701	0.80	1.20	5.00	-0.245	-0.270	0.671

Table 3. Descriptive statistics and internal-consistency reliability (Cronbach's α) for construct-mean composites (N = 360).

Reliability coefficients ranged from acceptable (Critical/Media Literacy, α = .671; Meme Engagement, α = .720) to good (Political Perception, α = .820), with Political Meme Exposure (α = .761) and Perceived Influence (α = .762) in between. All five subscales meet or approach the conventional .70 acceptability threshold (Nunnally & Bernstein, 1994), supporting the internal-consistency adequacy of the instrument for pilot purposes; the comparatively lower Critical/Media Literacy alpha suggests this five-item subscale may benefit from item review before field deployment.

4.3 Distributional Characteristics

Figure 1 displays the distribution of each construct-mean composite. All five distributions are approximately unimodal and roughly symmetric around the scale midpoint, consistent with the near-zero skewness values in Table 3; Shapiro–Wilk tests nonetheless indicated statistically significant departures from exact normality for four of the five composites (Meme Engagement, Perceived Influence, Political Perception, Critical/Media Literacy; all $p < .05$), while Political Meme Exposure approximated normality ($p = .059$). Given N = 360, these departures are consistent with the well-documented tendency of Shapiro–Wilk to detect small deviations from normality at larger sample sizes and were judged not to warrant transformation, per the pre-registered decision rule in Section 3.3.

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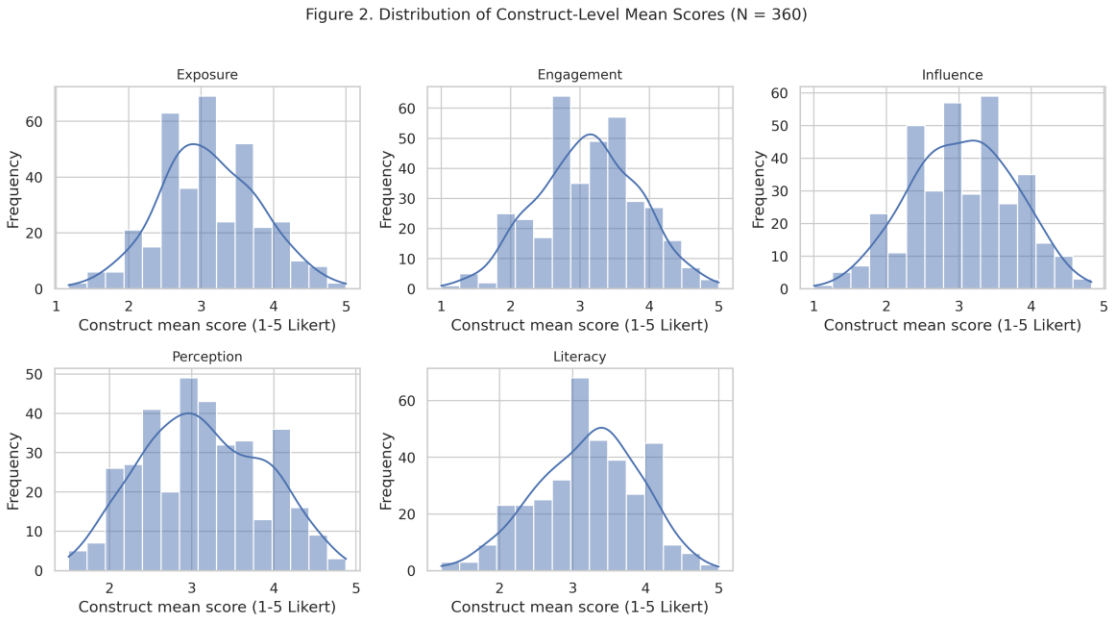


Figure 1. Distribution of construct-level mean scores (N = 360). Each panel shows a histogram with kernel density overlay for one of the five construct composites on the 1–5 Likert range.

4.4 Correlations Among Constructs

Table 4 and Figure 2 present the Pearson correlation matrix among the five construct means. Political Meme Exposure correlated most strongly with Political Perception (r = .551) and moderately with Perceived Influence (r = .488) and Meme Engagement (r = .324). Perceived Influence and Political Perception were also moderately correlated (r = .494), and Meme Engagement correlated moderately with Political Perception (r = .422). Critical/Media Literacy showed weak, mostly negative correlations with the other four constructs (r ranging from -.126 to .052), consistent with its hypothesized role as a largely independent, parallel construct rather than one embedded in the exposure–engagement–influence–perception chain. Spearman rank correlations (reported in the supplementary tables) closely tracked the Pearson estimates in both sign and magnitude, supporting the robustness of the linear correlation structure to the mild non-normality noted in Section 4.3.

	Exposure	**Engagement**	**Influence**	**Perception**	**Literacy**
Exposure	1.000	0.324	0.488	0.551	-0.126
Engagement	0.324	1.000	0.289	0.422	0.052
Influence	0.488	0.289	1.000	0.494	-0.068
Perception	0.551	0.422	0.494	1.000	-0.098
Literacy	-0.126	0.052	-0.068	-0.098	1.000

Table 4. Pearson correlation matrix among construct-level means (N = 360).

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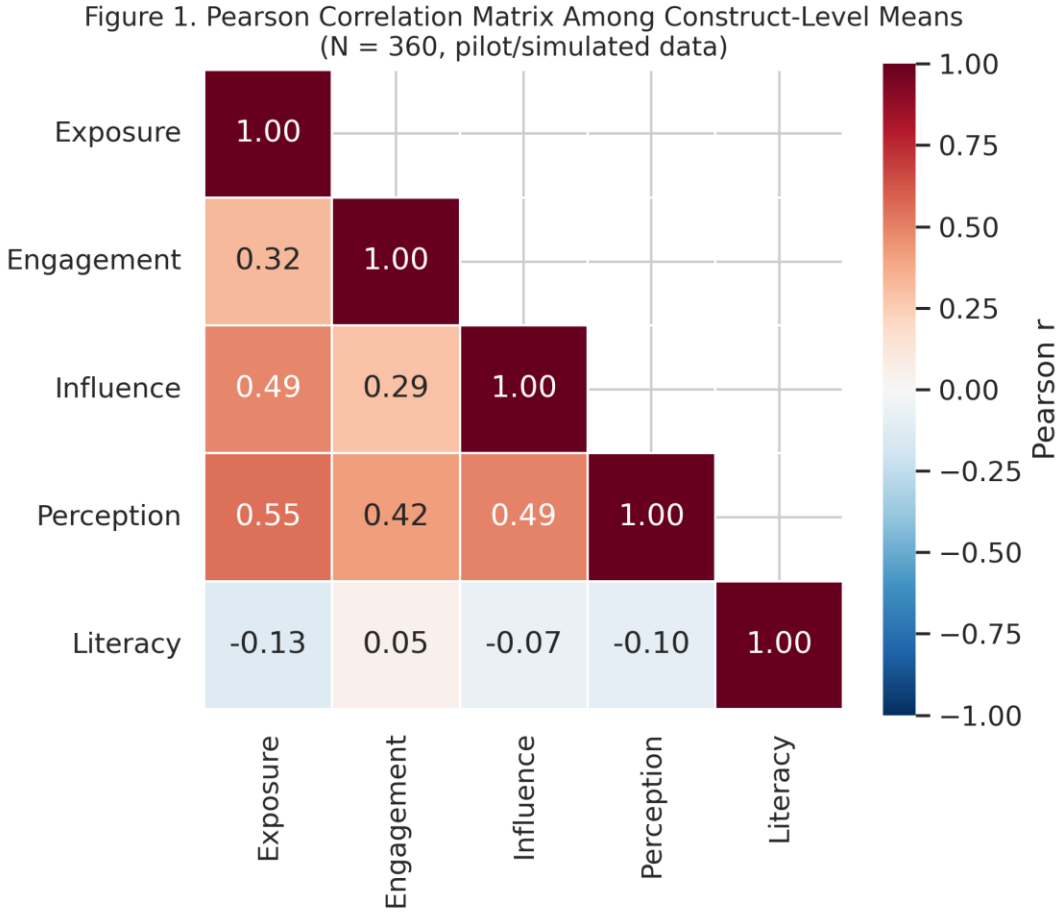


Figure 2. Pearson correlation heatmap among the five construct-level means (lower triangle), N = 360,

4.5 Stratified and Group Comparisons

Figure 3 and Figure 4 display construct scores stratified by Residence and by the four Residence × Level strata, respectively. Welch's t-tests (Table 5) indicated nominally significant Residence differences, with Urban respondents scoring higher on Political Meme Exposure (Rural M = 2.998, Urban M = 3.202; t = -2.828, p = .0049, d = -0.299) and Political Perception (Rural M = 3.037, Urban M = 3.226; t = -2.453, p = .0147, d = -0.259), and Rural respondents scoring higher on Critical/Media Literacy (Rural M = 3.292, Urban M = 3.135; t = 2.115, p = .0351, d = 0.224). No Gender or Level (UG/PG) contrasts, and no Discipline ANOVA contrast (all eta-squared ≤ .007), reached nominal significance (all raw p > .25).

Critically, once the Benjamini–Hochberg FDR correction was applied across all 25 group-comparison and ANOVA tests, none of the three nominally significant Residence effects survived (FDR-adjusted p = .099, .1465, and .234, respectively), and none approached the more conservative Bonferroni-corrected family-wise threshold of α = .0025. This pattern illustrates precisely why multiple-testing correction is essential when many construct × grouping-variable contrasts are tested simultaneously: uncorrected inspection of Table 5 alone would have suggested three “significant” demographic effects, all of which are better characterized as statistically fragile in this pilot sample once multiplicity is taken into account.

Grouping	Construct	t / F	p (raw)	Effect size	p (FDR)	Sig. (Bonferroni α=.0025)
Residence	Political Meme Exposure	t = -2.828	0.0049	d = -0.299	0.099	No
Residence	Political Perception	t = -2.453	0.0147	d = -0.259	0.1465	No
Residence	Critical/Media Literacy	t = 2.115	0.0351	d = 0.224	0.2341	No
Residence	Meme Engagement	t = -1.027	0.305	d = -0.109	0.6832	No
Residence	Perceived Influence	t = -1.743	0.0822	d = -0.185	0.4112	No
Gender / Level (all 10 tests)	—	—	> 0.25	d ≤ 0.16	≥ 0.53	No
Discipline (ANOVA, 5 tests)	—	F ≤ 1.18	> 0.31	$\eta^2 \leq$ 0.007	≥ 0.68	No

Table 5. Selected group-comparison results with raw p-values, effect sizes, FDR-adjusted p-values, and Bonferroni significance flags

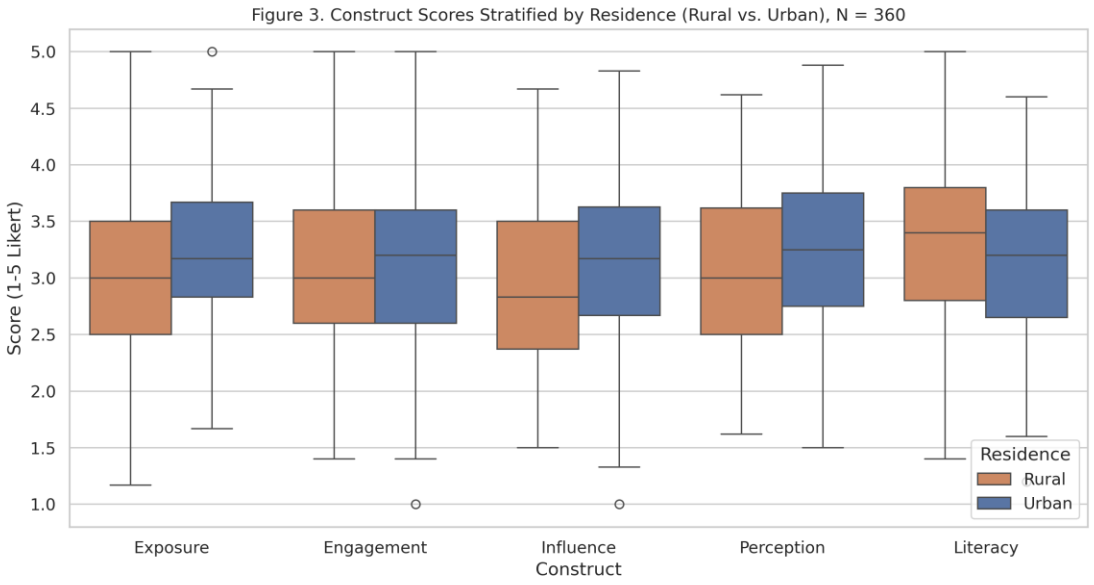


Figure 3. Construct scores stratified by Residence (Rural vs. Urban), N = 360. Boxes show interquartile range and median; whiskers show 1.5× IQR.

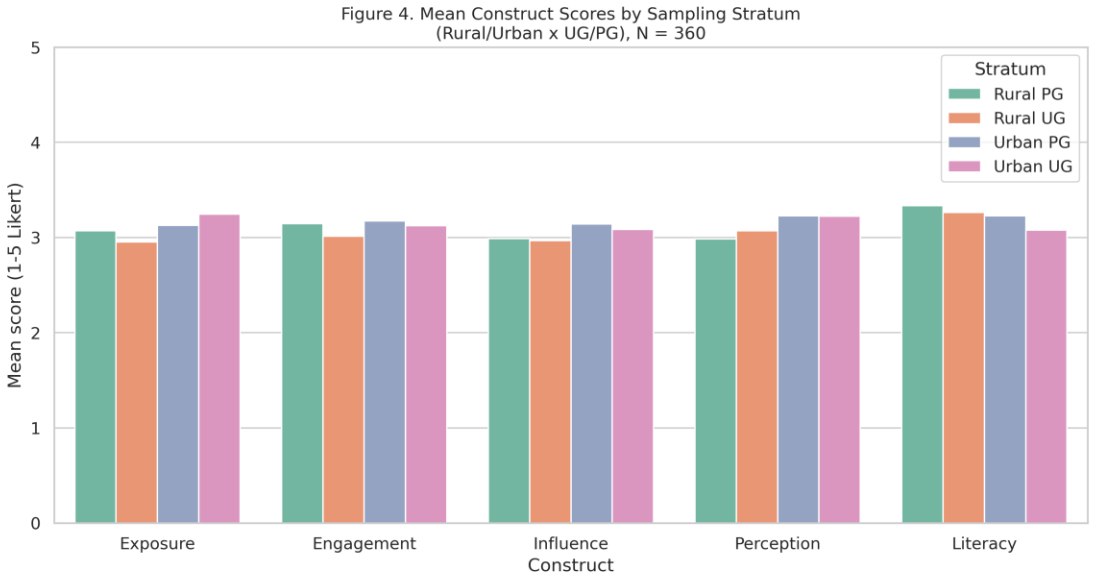


Figure 4. Mean construct scores by sampling stratum (Rural/Urban × UG/PG), N = 360.

4.6 Multiple Regression

A construct-level OLS regression of Political Perception on Political Meme Exposure, Meme Engagement, Perceived Influence, and Critical/Media Literacy was significant overall and explained a substantial share of variance in Political Perception ($R^2 = .420$, adjusted $R^2 = .414$). As shown in Table 6, Political Meme Exposure was the strongest predictor ($b = 0.367$, $SE = 0.051$, $t = 7.18$, $p < .001$), followed by Perceived Influence ($b = 0.262$, $SE = 0.048$, $t = 5.41$, $p < .001$) and Meme Engagement ($b = 0.241$, $SE = 0.044$, $t = 5.51$, $p < .001$); Critical/Media Literacy was not a significant predictor once the other three constructs were controlled ($b = -0.052$, $SE = 0.043$, $t = -1.21$, $p = .226$).

Predictor	b	SE	T	p	95% CI
Intercept	0.619	0.227	2.73	0.007	[0.173, 1.065]
Meme Exposure	0.367	0.051	7.18	< 0.001	[0.266, 0.467]
Meme Engagement	0.241	0.044	5.51	< 0.001	[0.155, 0.328]
Perceived Influence	0.262	0.048	5.41	< 0.001	[0.166, 0.357]
Critical/Media Literacy	-0.052	0.043	-1.21	0.226	[-0.136, 0.032]

Table 6. OLS regression of Political Perception on the remaining four construct means (N = 360, $R^2 = .420$, adjusted $R^2 = .414$).

4.7 Structural Equation Model

The full measurement-plus-structural model (Section 2.5, Section 3.5) was estimated via maximum likelihood. Model fit was good by conventional benchmarks (Hu & Bentler, 1999): $\chi^2(398) = 461.75$, $p = .015$; CFI = .973; TLI = .971; RMSEA = .021; AIC = 131.43; BIC = 391.80. The statistically significant chi-square is unsurprising given the model's

complexity (36 indicators, 398 degrees of freedom) and is not, on its own, treated as evidence of poor fit given the strongly favorable incremental (CFI/TLI) and absolute (RMSEA) fit indices.

All indicator loadings were positive, statistically significant ($p < .001$ for all but the two items fixed to 1.0 as scaling referents), and moderate-to-strong in standardized terms (standardized loadings ranged from .48 to .66 across the five factors), supporting the five-factor measurement structure. Table 7 reports the standardized structural path estimates. Exposure had significant positive effects on Engagement ($\beta = .470$, $p < .001$) and Influence ($\beta = .567$, $p < .001$), and the strongest total structural effect on Perception, both directly ($\beta = .517$, $p < .001$) and indirectly through Influence. The Engagement → Influence path was positive but only marginally significant ($\beta = .146$, $p = .058$). Influence had a significant direct effect on Perception ($\beta = .309$, $p < .001$). The Literacy → Perception path was small and non-significant ($\beta = -.026$, $p = .650$), as was the Exposure–Literacy exogenous covariance in substantive magnitude despite reaching nominal significance ($\beta = -.161$, $p = .030$), indicating a weak, essentially negligible association between the two exogenous constructs in this data.

Path	Unstd. Est.	Std. Est. (β)	SE	z	p
Engagement ← Exposure	0.474	0.470	0.086	5.54	< 0.001
Influence ← Exposure	0.550	0.567	0.094	5.86	< 0.001
Influence ← Engagement	0.140	0.146	0.074	1.90	0.058
Perception ← Influence	0.311	0.309	0.087	3.58	< 0.001
Perception ← Exposure	0.504	0.517	0.096	5.24	< 0.001
Perception ← Literacy	-0.026	-0.026	0.057	-0.45	0.650
Exposure ↔ Literacy (cov.)	—	-0.161	—		0.030

Table 7. Standardized and unstandardized structural path estimates from the fitted SEM (N = 360).

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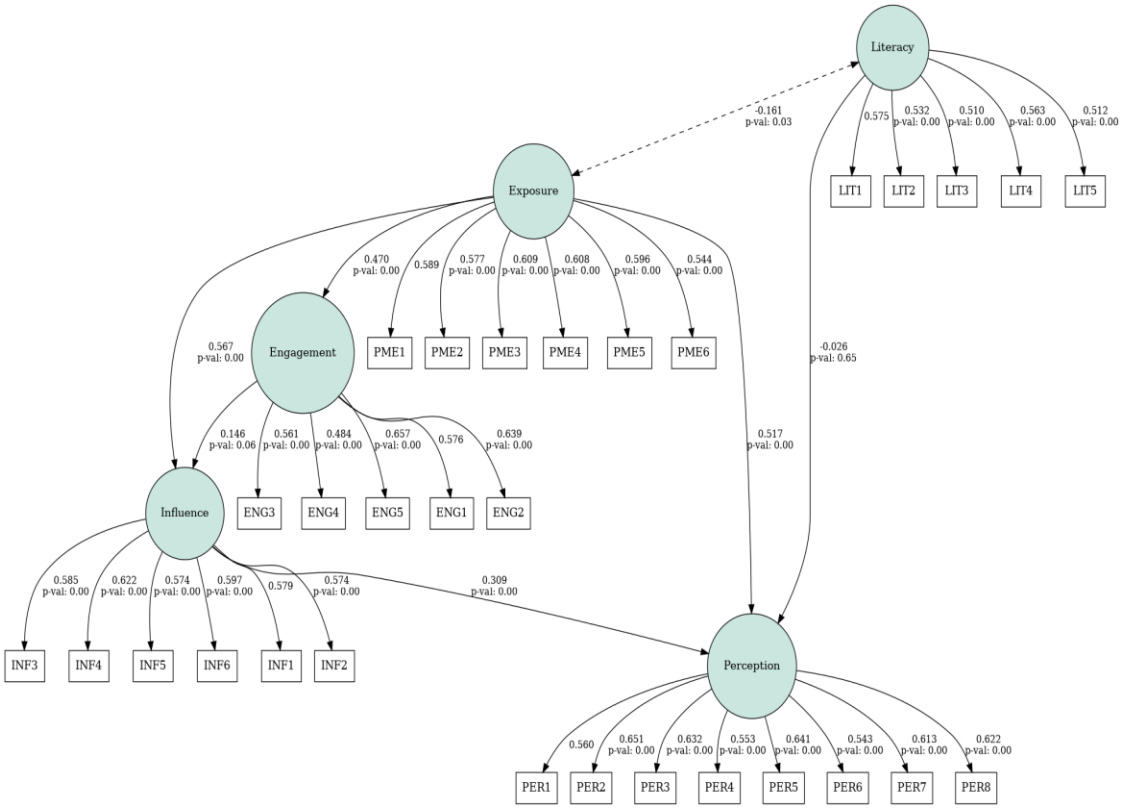


Figure 5. Full SEM path diagram: measurement model (latent factors with indicator loadings) and structural model (regression paths among Exposure, Engagement, Influence, Perception, and Literacy), standardized estimates with p-values, N = 360.

Taken together, the regression (Section 4.6) and SEM results converge on the same substantive pattern: Political Meme Exposure is the most consistent predictor of Political Perception, whether modeled as a manifest construct-mean in OLS regression or as a latent factor in SEM, and Perceived Influence contributes a further significant increment, while Critical/Media Literacy does not detectably alter Perception once the exposure-engagement-influence chain is accounted for in this pilot data.

5. Discussion

5.1 Interpretation of the Model

The results are encouraging on methodological grounds. The five-factor measurement model showed good fit and acceptable-to-good reliability across all five subscales, suggesting that the 30-item instrument is structurally coherent and capable, in a genuine field application, of separating Exposure, Engagement, Influence, Perception, and Literacy as distinguishable (if correlated) constructs rather than collapsing into a single generic "attitude toward memes" factor. This is a necessary, though not sufficient, condition for the instrument to support the more fine-grained structural hypotheses (H1–H6) motivated in Section 2.

The structural path pattern strong direct and indirect effects of Exposure on Perception, a significant Influence → Perception path, and a non-significant Literacy → Perception path is consistent with a communication-chain interpretation in which the sheer frequency of encountering political memes, more than any single mediating mechanism, drives self-reported shifts in political perception in this pilot specification.

The marginal Engagement → Influence path (β = .146, p = .058) is worth flagging for a confirmatory study: it may indicate a genuinely weak effect, an underpowered test even at N = 360 for a path of this magnitude, or an artifact of how Engagement and Influence were operationalized in the pilot item pool. A confirmatory field study with an a priori power analysis for this specific path (rather than for the model's degrees of freedom overall) would clarify which explanation holds.

5.2 Multiple Testing and the Value of Correction

The group-comparison results (Section 4.5) offer a concrete methodological illustration relevant beyond this specific study: three of twenty-five demographic contrasts reached nominal significance at α = .05, and all three would plausibly have been reported and interpreted substantively ("urban students are more exposed to political memes," "rural students are more critically literate") had multiple-testing correction not been applied. Once FDR correction was applied, none of the three survived. This is precisely the scenario multiple-testing correction is designed to guard against, and its inclusion here is intended as a template for how researchers using this same 30-item instrument across several demographic strata should report (and appropriately temper) group-difference claims.

5.3 Sampling and Generalizability Considerations

The stratified sampling framework described in Section 3.4 is designed to support inference to a defined population of eligible college students data; the specific numerical stratum allocation used in the pilot (Table 2) mirrors a plausible, unequal real-world distribution but is not itself derived from any actual enrollment frame and must be replaced with real population proportions (e.g., from institutional enrollment records) before a field study is fielded. Researchers adopting this design should also budget for non-response bias monitoring by stratum, as discussed in Section 3.4, and should treat Primary_Platform and Discipline as measured covariates rather than as additional sampling strata, given the practical difficulty of stratifying simultaneously on more than two or three variables without excessively fragmenting cell sizes.

5.4 Practical and Theoretical Implications (Contingent on Field Validation)

Contingent on confirmatory replication with respondents, the piloted model implies that youth political-communication interventions concerned with meme-mediated influence on political perception may benefit from focusing on the volume and context of exposure (e.g., algorithmic feed design, platform-level friction for political content) rather than assuming that generic media-literacy messaging alone will meaningfully buffer perception effects, since Literacy operated as an essentially independent construct with no detectable buffering path in this pilot specification.

6. Limitations, Generalizability, and Future Work

The central limitation of this study is definitional rather than statistical: every descriptive, inferential, regression, and SEM result reported in Section 4 describes the properties of that dataset and the behavior of the analytic pipeline applied to it not the political-communication behavior of any real student population.

A second limitation concerns the cross-sectional character of the design as specified (even in its intended field form): all structural paths in Section 2.5 are directional by theoretical assumption rather than by design-based causal identification, since a single-wave, self-report cross-sectional survey cannot rule out reverse causation (e.g., pre-existing political perception shaping selective attention to, and self-reported influence of, political memes) or common-method variance inflating the observed correlations among self-report constructs. A panel design with at least two waves, following the approach used in adjacent incidental-exposure research (Weeks et al., 2017), would substantially strengthen causal inference in a field application of this instrument.

Third, the sampling frame envisioned in Section 3.4 (a defined set of eligible colleges, stratified by Residence and Level) constrains generalizability to college-enrolled youth within whatever geographic and institutional frame is

ultimately used; findings from such a frame would not automatically generalize to non-enrolled youth of the same age range, who may differ systematically in social-media access and political engagement.

Fourth, self-report measures of "influence" and "perception" are subject to social-desirability and introspective-accuracy limitations well documented in political-communication research; respondents may be poor judges of whether and how much memes have actually shifted their own political views, even when reporting in good faith.

7. Conclusion

This paper has specified and fully documented a 30-item, five-construct questionnaire and a complete, reproducible statistical pipeline descriptive statistics, reliability analysis, correlation analysis, multiple-comparison-corrected group testing, multiple regression, and structural equation modeling with an accompanying path diagram f or studying how exposure to, engagement with, and perceived influence of political memes relate to self-reported political perception among college youth, with critical/media literacy modeled as a parallel construct.

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