Personalization Algorithms and Their Influence on Political Awareness: A Critical Review, Conceptual Framework and Proposed Research Design

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Abstract — Recommender systems increasingly determine what people encounter about public affairs. This paper reviews how personalization algorithms may influence political awareness, treated as a multidimensional construct comprising political knowledge, perceived viewpoint diversity, awareness of algorithmic curation and political engagement. An integrative narrative review compares peer-reviewed experiments and audits, a national survey report and regulatory texts, and explains how two-stage ranking pipelines and feedback loops generate political exposure. The evidence indicates that ranking reliably changes what users see and can give some political actors and sources more visibility than others. Large Facebook and Instagram experiments found no significant short-term changes in polarization or political knowledge, whereas a 2026 field experiment on X found shifts in selected issue-specific attitudes without changes in partisanship or affective polarization. Evidence from India and short-video platforms is limited. The paper proposes the Algorithmic Exposure–Awareness Model (AEAM), maps its propositions to four hypotheses, and outlines a proposed survey and experiment with a scenario-based algorithmic-literacy module. No primary data were collected and all hypotheses remain untested. The central concern is uneven, opaque exposure whose consequences depend on users, platforms and context.

Keywords — algorithmic personalization; recommender systems; political awareness; filter bubbles; echo chambers; social media

I. INTRODUCTION

Political information increasingly reaches people through platforms rather than through editors. A recommender system selects and orders what appears on a screen using signals such as past behavior, social connections and context. This process is commonly called personalization, and it embodies assumptions about what counts as relevant [1]. Similar ranking logic operates in social feeds, video recommendations, search results and news aggregators.

Public concern was shaped by the "filter bubble" thesis, which holds that tailored feeds narrow exposure and isolate people from opposing views [2]. Related "echo chamber" arguments warn that like-minded communities can weaken the shared factual environment on which democratic discussion relies [3]. The empirical record is more complicated. Early platform data showed that users' own click choices limited cross-cutting exposure more than ranking did [4]. Large experiments around the 2020 United States election changed what users saw but detected little short-term change in several attitude and knowledge outcomes [5], [6]. A 2026 experiment on X found a different pattern, with effects on selected issue-specific attitudes but not on partisanship or affective polarization [7].

This paper treats political awareness as a multidimensional concept rather than a single score. Its dimensions are political knowledge, perceived viewpoint diversity, awareness of algorithmic curation and political engagement. Awareness of curation is included because users who do not know that a feed is selected and ranked may be less able to judge what it omits [8]. Evidence for India is limited to a 2019 survey of English-speaking online news users, which described a mobile-first, platform-dominated environment with limited awareness of algorithmic curation [9]. Most experimental evidence remains United States-centred [10].

A. Problem statement and objectives

Personalization shapes what citizens see about public affairs, yet its workings are opaque, its effects are contested, and many users do not understand it. Definitions of echo chambers and filter bubbles differ across studies, which produces conflicting conclusions [11], [10]. Few testable

models link exposure to awareness, and few learning interventions target algorithmic understanding. The paper has the following objectives:

- To explain how personalization pipelines produce political exposure, including the role of feedback loops.
- To compare evidence on exposure diversity, amplification, polarization, political knowledge and algorithmic awareness.
- To propose a conceptual framework, the Algorithmic Exposure–Awareness Model (AEAM), and a research design that can test parts of it.
- To derive educational, platform and policy implications without overstating causality.

Four research questions guide the review. **RQ1:** How does personalization change the diversity and visibility of political content users encounter? **RQ2:** What do experiments show about effects on polarization, political knowledge and attitudes? **RQ3:** How aware are users of algorithmic curation, and does awareness matter? **RQ4:** What educational and policy measures can support informed engagement?

B. Contributions

The paper offers (i) an integrative comparison of evidence, including 2026 findings from X; (ii) AEAM, which places exposure and awareness in one testable chain; (iii) a mapping from framework propositions to hypotheses, variables and analyses; and (iv) an educational module concept. It reports no primary data, and the framework and hypotheses are proposed and unvalidated. The remainder of the paper is organised as follows. Section II reviews related work and technical background. Section III describes the review methodology, the proposed AEAM framework and the proposed research design. Section IV presents the evidence synthesis, discussion, implications and limitations. Section V concludes and outlines future work.

II. RELATED WORK

A. How personalization pipelines produce exposure

Large recommender systems are commonly built in stages. A published description of YouTube's system divides the problem into a candidate-generation model, which narrows a very large corpus to a small set of items per user, and a ranking model, which scores those candidates [12]. Platform pipelines are proprietary and differ in detail, so this paper uses the two-stage description as an illustration and not as a claim about any particular platform's current system.

Such systems learn from implicit behavioural signals such as watches, clicks, follows and searches. Ranking objectives are typically tied to predicted engagement, although the exact objectives are not public. Items are therefore ordered by estimated relevance to a user's profile rather than by editorial judgement [1]. Because the output is a ranked list, small differences in scores translate into large differences in visibility, which makes ranking a natural point at which political content can be amplified or demoted.

The system also forms a loop. What users see shapes what they click, and clicks become new training data. Whether this loop narrows political exposure over time is an empirical question that the cited experiments only partly address, because they intervene for weeks or months and not over years [5], [7]. AEAM makes this loop explicit in Section III-B.

B. Key concepts

Nguyen separates an *epistemic bubble*, in which relevant voices are omitted, from an *echo chamber*, in which outside voices are actively discredited [13]. Zuiderveen Borgesius *et al.* distinguish *self-selected* personalization, chosen by users, from *pre-selected* personalization, imposed by systems [14]. *Algorithmic amplification* is the extra visibility some content receives relative to a non-personalized baseline such as a chronological feed [15]. *Algorithmic awareness* is knowing that content is curated, understanding broadly how, and being able to act on that knowledge [8]. The "algorithmic imaginary" describes the beliefs people hold about algorithms, which shape how they use platforms [16].

Normative theory adds a further layer. Helberger argues that news recommenders should be judged against different models of democracy, such as liberal, participatory and deliberative models [17]. A finding of "no strong effect on attitudes" therefore does not settle whether personalization is a democratic problem.

C. Exposure and viewpoint diversity

Early studies tested the filter-bubble claim by measuring exposure. An analysis of 10.1 million U.S. Facebook users found that ranking modestly reduced cross-cutting content, while users' own clicks reduced it more [4]. Browsing data showed that social media and search were linked to more ideologically separated news consumption and also to more contact with opposing views [18]. In a national survey, people with high political interest and diverse media use were less likely to be in an echo chamber [19]. These studies agree that personalization does not isolate everyone uniformly. They differ in what they measure: platform logs, browsing histories or self-reported media diets.

D. Algorithmic amplification

A randomised holdout of about two million daily Twitter accounts compared algorithmic and reverse-chronological timelines. The mainstream political right was amplified more than the mainstream left in six of seven countries, and right-leaning news sources were amplified in the United States [15].

Amplification here is measured against the chronological baseline and describes outcomes, not intent. An analysis of 208 million U.S. Facebook users found that ideological segregation in news rose from potential exposure to actual exposure and engagement [20]. These results show that default ranking affects who gains visibility, which is distinct from whether individual users become more polarized.

E. Attitudes, political knowledge and engagement

In a three-month Facebook and Instagram experiment, moving users to a chronological feed did not significantly change issue polarization, affective polarization or political knowledge [5]. In a companion experiment, reducing exposure to like-minded sources had no measurable effect on polarization [6]. Following accounts with opposing views did not reduce polarization in a Twitter experiment and was associated with more conservative attitudes among Republicans [21]. Counter-attitudinal news reduced negative feelings toward the opposing party in a Facebook field experiment [22].

More recent evidence from X adds nuance. In a seven-week field experiment with about 5,000 active U.S. users run in 2023, switching from a chronological to the algorithmic feed increased engagement and shifted several policy priorities and views on current political events in a more conservative direction. Switching the algorithm off for users who had been on it did not produce comparable reverse effects, and neither change significantly affected polarization or partisanship [7]. The authors' content analysis indicated that the algorithm promoted conservative and activist posts and demoted posts by traditional media, and that the effect persisted partly because users followed more conservative accounts [7]. The study suggests that effects depend on the platform, the outcome and the direction of the intervention. It should not be read as a universal effect or assumed to apply to Indian users.

One caution applies to the Meta-platform study. It has two published errata. The 2024 erratum concerns Instagram variables for exposure to untrustworthy sources, where data from accounts deleted before the dataset was built had been excluded because of a processing error [23]. The 2026 erratum clarifies that carousel and non-carousel Instagram posts were not distinguished and revises the description of the Instagram feed metrics, and it states that the correction cannot be applied to the original estimates with certainty [24]. This paper therefore relies on the reported attitude and knowledge outcomes and treats Instagram-specific exposure magnitudes as provisional.

At review level, evidence supports clear effects of ranking on exposure and weaker, more heterogeneous effects on attitudes [11], [10]. Evidence on participation is thin and mostly limited to secondary outcomes of the experiments above.

F. Algorithmic awareness and literacy

Many Facebook users in an early study did not realise that their News Feed was filtered, and discovering this changed how they thought about the platform [8]. For India, a YouGov online survey of 1,013 English-speaking internet users in January 2019 reported limited awareness that algorithms curate news [9]. The sample excludes non-English users and people offline and cannot represent the Indian public. No study located for this review tests whether improving awareness changes political outcomes.

Research on scenario-based and game-based learning suggests ways of building awareness, although none addresses algorithms directly. Branching scenarios improved elementary students' decision-making but not scientific literacy [25]. A simulation game helped college students analyse information-ethics problems such as privacy [26], and digital game-based learning improved digital-etiquette literacy in a primary-school quasi-experiment [27]. Reviews report benefits that vary by context and uncertain effects overall [28], [29]. Learners respond differently to the same game elements [30], and extra features do not always add benefit [31], [32]. These findings support testing a module, not assuming that it works.

G. Research gaps

TABLE I. SUMMARY OF KEY STUDIES AND THEIR LIMITS

Study	Design and sample	Main finding	Limit for this paper
Bakshy et al. [4]	Observational; 10.1 M U.S. Facebook users	User choice limited cross-cutting exposure more than ranking	U.S.; platform-employed authors
Flaxman et al. [18]	Browsing histories, U.S.	Separation and cross-exposure can rise together	Browsing data only
Dubois & Blank [19]	National survey, U.K.	Interest and media diversity lower echo-chamber risk	Self-reported media use
Bail et al. [21]	Twitter field experiment	Opposing views did not reduce polarization	U.S.; short window
Levy [22]	Randomised Facebook experiment	Counter-attitudinal news reduced negative affect	U.S. only
Huszár et al. [15]	Randomised holdout, ~2 M daily accounts	Amplification favoured mainstream right in 6 of 7 countries	Chronological baseline; platform-employed authors

Study	Design and sample	Main finding	Limit for this paper
Guess et al. [5]	3-month experiment, Facebook and Instagram	No significant change in polarization or knowledge	Short window; errata on Instagram metrics
Nyhan et al. [6]	Experiment, 23,377 Facebook users	Less like-minded exposure had no measurable polarization effect	U.S.; short window
González-Bailón et al. [20]	Aggregated data, 208 M U.S. users	Segregation rose from potential to actual exposure	Aggregated; U.S.
Gauthier et al. [7]	7-week field experiment, ~5,000 active U.S. X users	Algorithm on shifted some policy attitudes; no polarization effect; off had no comparable effect	U.S.; short window; asymmetric effects
Eslami et al. [8]	Qualitative and survey study	Many users unaware of curation	Facebook only; dated
Aneez et al. [9]	Online survey, n = 1,013, India	Limited awareness of curation	English-speaking online users
Hartmann et al. [10]	Systematic review, 129 studies	Conclusions depend on definitions and methods	U.S.-centred literature

Five gaps follow. First, definitions and measures of echo chambers differ, so results are hard to compare. Second, evidence is concentrated in the United States and on a few platforms, with short-video and messaging environments under-studied. Third, few studies treat awareness as both a moderator and an outcome, and none located tests an intervention to improve it. Fourth, no single testable framework links personalization inputs, exposure, user processing and political outcomes. Fifth, the only national-scale evidence located for India is a 2019 survey of English-speaking online users.

III. METHODOLOGY

A. Review methodology

The study is an *integrative narrative review*. It is not a systematic review and does not follow PRISMA. Sources were identified from the authors' working draft and reading list, and each record was then checked against publisher, DOI and journal pages. The authors did not log database names, search strings, dates or screening counts, so the search cannot be reproduced and no claim of comprehensiveness is made.

Sources were retained when they (i) addressed personalization, ranking or recommendation in relation to political information, or scenario-based and game-based learning; (ii) were peer-reviewed or issued by an established academic or regulatory body with a traceable DOI or official link; and (iii) were published between 2011 and 2026. Opinion pieces without evidence, studies of purely commercial advertising and sources whose authorship or venue could not be verified were excluded. Each source was appraised on design, sample, platform data access, outcome measurement and consistency with other studies. Randomised experiments and audits were given more causal weight than observational and survey designs, and conceptual works were used for definitions and normative argument only. Several key studies involved platform employees or cooperation [4], [5], [15], [6], which limits independent verification of platform-side data.

A future survey and controlled experiment are proposed because the review cannot answer, from published studies alone, how awareness relates to source diversity among Indian students or whether a learning module improves feed evaluation. These questions require primary data.

B. The Algorithmic Exposure–Awareness Model (AEAM)

AEAM is a proposed conceptual framework derived from the reviewed literature. It has not been empirically validated. It describes personalization as five linked components (Fig. 1), moderated by user and platform characteristics and closed by a feedback loop. Each arrow represents a hypothesised relationship that is either supported by cited studies or left as a proposition for testing.

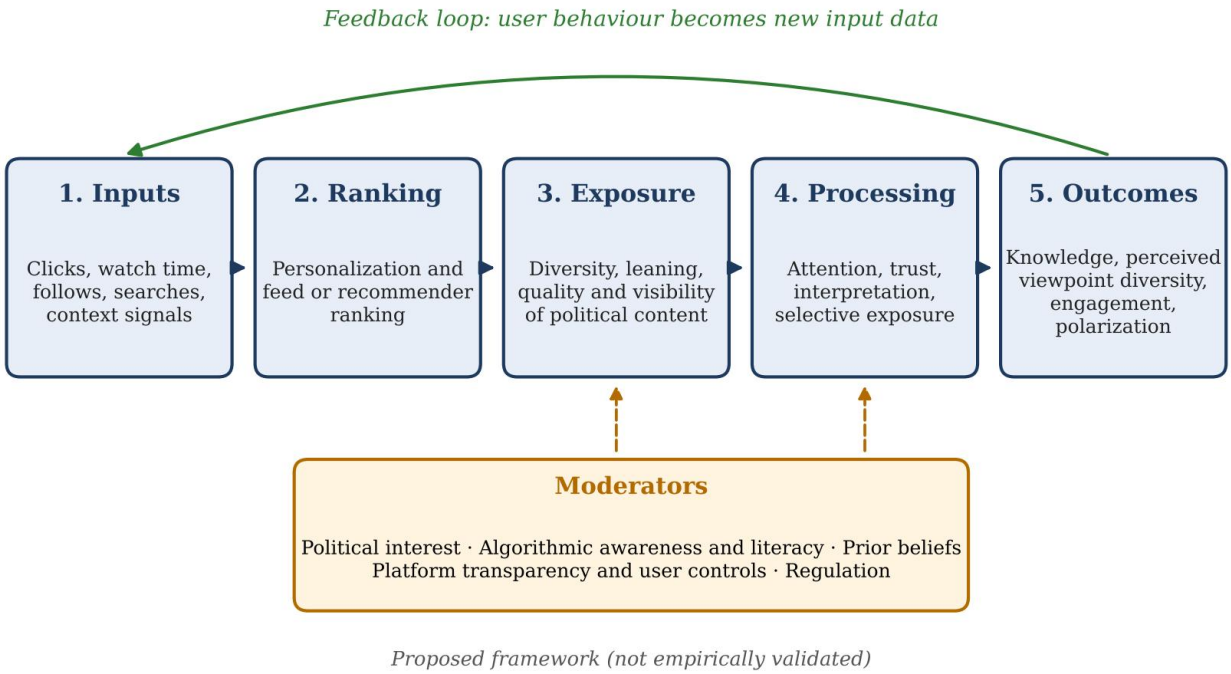

Fig. 1. The Algorithmic Exposure–Awareness Model (AEAM): a proposed and unvalidated conceptual framework.

TABLE II. AEAM COMPONENTS, BASIS AND INDICATORS IN THE PROPOSED DESIGN

Component	Definition	Basis	Indicator in proposed design
1. Inputs	Clicks, watch time, follows, searches and context signals that form a user profile	[1], [12]	Self-reported platform use (not logged)
2. Ranking	Scoring and ordering of candidate items, often tied to predicted engagement	[12], [15]	Not measured; reviewed only
3. Exposure	Diversity, leaning, quality and visibility of political content a user sees	[4], [5], [7]	Reliance on feeds; news-source diversity; perceived viewpoint diversity
4. Processing	Attention, trust, interpretation and selective exposure	[13], [16]	Algorithmic awareness; feed-evaluation task
5. Outcomes	Political knowledge, perceived viewpoint diversity, participation, polarization	[5], [19]	Knowledge score; participation; perceived polarization
Moderators	Political interest, awareness, literacy, prior beliefs, platform transparency, regulation	[19], [8], [17]	Political interest; awareness scale
Feedback loop	User behaviour becomes new input data and may reinforce or weaken later exposure	[12]	Not tested; requires longitudinal data

AEAM introduces no new constructs. Its contribution lies in three combinations. First, it places exposure and awareness in one chain, so the same feed can be expected to produce different outcomes depending on what the user notices and understands. Second, it treats awareness as both a moderator and a possible outcome of intervention. Third, it makes the feedback loop explicit. Links from ranking to exposure are well documented, links from exposure to attitudes are weaker and heterogeneous, and links involving awareness and literacy are least tested, which is where the proposed design focuses. Validation would require survey measurement, experimental manipulation of awareness, longitudinal data for the feedback loop and platform audits for the ranking stage.

C. Propositions, hypotheses and proposed design

This section describes a **proposed** study that has not been conducted. No survey was administered, no participants were recruited, no ethical approval has been sought, and the hypotheses are untested.

Not every AEAM proposition can be tested with a survey and a small experiment. Table III shows which propositions the design tests and which rest on the review alone.

TABLE III. MAPPING OF AEAM PROPOSITIONS TO HYPOTHESES AND PROPOSED TESTS

Proposition	Hypothesis	Variables	Measurement	Analysis

Proposition	Hypothesis	Variables	Measurement	Analysis
P1: Personalization changes exposure more reliably than attitudes	Not tested; review-based	Ranking, exposure, attitudes	Needs platform experiments	None in this design
P2: User choice and networks shape exposure at least as much as ranking	Not tested; review-based	Choice, network, ranking	Needs platform or audit data	None in this design
P3a: Awareness is linked to wider source diversity	H1: awareness is positively associated with source diversity	IV: awareness; DV: source diversity	Scales A3 and A4 (Appendix)	Correlation; regression with controls
P3b: Reliance is linked to narrower diversity, moderated by interest	H2: reliance is negatively associated with diversity. H3: political interest moderates H2	IV: reliance; DV: diversity; moderator: interest	Scales A2, A4, A5	Regression with interaction term; simple slopes
P4: Amplification is uneven across political actors	Not tested; review-based	Amplification, actors	Needs platform audits	None in this design
P5: Scenario-based learning improves awareness-related skills	H4: module group outperforms information-only control on feed evaluation	IV: condition; DV: task score; covariate: pre-test	Feed-evaluation task A7, pre and post	ANCOVA on post-test with pre-test covariate

Political knowledge, participation and perceived polarization are exploratory outcomes not tied to a hypothesis. Source diversity and perceived viewpoint diversity are self-reported and are distinct from objectively observed exposure, which would require platform-level behavioural data.

D. Participants, sampling and sample size

The proposed population is university students and young adults aged 18 to 25 who use social or video platforms for news. No sampling frame exists for this population, so the study would use purposive quota sampling across discipline, gender, language of news use and institution. A margin-of-error claim such as ±5% at 95% confidence assumes probability sampling and cannot be made for a purposive sample, so no population-level margin of error will be reported. Results would describe the sample and be indicative only for similar students.

Sample size will be set by an a priori power analysis before recruitment, for example in G*Power. For H1 to H3 the analysis needs the smallest effect size of interest (f^2 for the regression and the interaction term), significance level, target power and number of predictors. For H4 it needs the smallest effect size of interest (Cohen's d or f), significance level, target power, the expected pre-test and post-test correlation and an attrition allowance. The authors must choose and justify these values. No power analysis has been completed and no sample size is claimed.

E. Instrument, experiment and analysis

The proposed questionnaire (Appendix A) measures platform reliance, algorithmic awareness, news-source diversity, political interest, political knowledge, participation, perceived viewpoint diversity and perceived polarization, and includes a scenario-based feed-evaluation task. It has not been administered. Before use it needs expert review, a pilot, and assessment of reliability (for example Cronbach's alpha and inter-rater agreement) and construct validity (for example exploratory then confirmatory factor analysis). None of these assessments has been done.

For H4, participants would be randomly assigned after a pre-test to a scenario-based module or an information-only control. Both groups would complete parallel versions of the feed-evaluation task before and after the activity, scored by two raters blind to condition. The simulated feeds would use fictional, neutral content and no real parties or candidates. H1 and H2 would be tested with multiple regression controlling for age, discipline and general media use, and H3 with a centred interaction term. H4 would compare post-test scores between conditions adjusting for pre-test scores. Effect sizes with confidence intervals would be reported, exploratory analyses labelled, and structural equation modelling of the full AEAM treated as future work requiring a larger validated sample.

F. Ethics and data protection

Approval from the institution's ethics committee would be required before recruitment, with informed consent, voluntary participation, anonymous responses and secure storage. India's Digital Personal Data Protection Act, 2023 [33] is being brought into force in phases. The Rules notified in November 2025 [34] bring institutional provisions into effect first, consent-manager provisions after one year and most remaining provisions after eighteen months, which is May 2027. The authors should confirm against the official Gazette which provisions apply on the date of data collection.

IV. RESULTS AND DISCUSSION

A. Evidence synthesis

No experiment or survey was conducted, so this section reports a synthesis of published results and not new results. Table IV separates what the literature establishes, what is mixed, what is interpretation and what remains hypothesis.

TABLE IV. STATUS OF CLAIMS DISCUSSED IN THIS PAPER

Status	Claim	Basis
Convergent evidence	Ranking changes what users see; user choice also shapes cross-cutting exposure	[4], [18], [5], [7]
Audit and platform studies	Default ranking can amplify some political actors and sources more than others relative to a baseline	[15], [20]
Mixed, outcome-dependent	Effects of exposure changes on attitudes, polarization and knowledge	[21], [22], [5], [6], [7]
Mixed, definition-sensitive	How common echo chambers are depends on definitions and measurement	[11], [10]
Limited evidence	Some users, including in India, have low awareness of curation; evidence is narrow and dated	[8], [9]
Interpretation	Awareness and political interest may explain why similar feeds yield different responses	[19]; proposed AEAM
Hypothesis, untested	Awareness is associated with source diversity; a scenario-based module improves feed evaluation	H1–H4; no primary data

B. Why changes in exposure do not necessarily change attitudes

Exposure describes what appears on a screen, whereas attitudes depend on what users notice, trust, interpret and remember. A feed change may alter content users scroll past or already discount. The Facebook and Instagram experiments found no detectable short-term change in several attitude and knowledge outcomes, while the X experiment found effects on selected issue-specific attitudes but not on partisanship or affective polarization [5], [6], [7]. These results are better understood as platform- and outcome-dependent than as one verdict on whether algorithms influence politics. Experiments last weeks or months, whereas attitudes may form over years.

C. Uneven amplification as a separate concern

Amplification findings raise a fairness question that does not depend on polarization. If default ranking gives some political actors or sources more reach than others [15], uneven visibility may shape competition for attention even when individual attitudes stay stable. This supports assessing recommenders against democratic values as well as engagement [17]. The evidence is specific to the platform and period studied.

D. Transferability to India

Most causal evidence comes from the United States and a few platforms [10]. India differs in party structure, language diversity, media institutions and platform mix, and the national-scale evidence located covers English-speaking online users in 2019 [9]. Effects among Indian users, including vernacular-language users and people relying on short-video and messaging platforms, remain unmeasured. U.S. findings should be treated as hypotheses for Indian settings.

E. Comparison with previous reviews

Earlier systematic reviews showed that conclusions about echo chambers depend on definitions and measurement [11], [10]. This paper adds a framework placing awareness alongside exposure, a mapping of propositions to a proposed design and an explicit separation of reviewed findings from untested hypotheses. It adds no new empirical evidence and is narrower in coverage than the reviews it draws on.

F. Implications for education

Because awareness appears limited and may be teachable, algorithmic literacy is a practical point of intervention. A scenario-based module would follow a cycle of situation, response options, decision, feedback, consequence and reflection. For example, a simulated feed shown after a fictional user repeatedly views one kind of political video would ask learners to identify personalization signals, notice missing viewpoints and choose ways to broaden their sources. Game elements should serve the learning goal [31], progress should not depend only on rankings [30], and effects should be evaluated before being claimed [29]. The module should collect only the data needed for learning and should not profile learners. Whether it works is the question H4 addresses.

G. Implications for platform design and regulation

The EU Digital Services Act contains two relevant provisions with different scope. Article 27 requires providers of online platforms to explain, in plain and intelligible

language in their terms and conditions, the main parameters of their recommender systems. Article 38 requires providers of very large online platforms and very large search engines that use recommender systems to offer at least one option for each system that is not based on profiling within the meaning of the General Data Protection Regulation [35]. The additional obligation applies only to services designated as very large and not to every platform. India's data-protection framework regulates personal-data processing [33], [34] and should not be described as equivalent to those recommender-system provisions.

Within these limits, the evidence supports plain-language explanation of ranking, meaningful user control over recommendation signals, design and audits that consider diversity and fair visibility alongside engagement, and privacy-protective access for vetted independent researchers. Access matters because several influential studies depended on platform cooperation and because independent audits are needed as systems change [10].

H. Limitations

- **Review method:** the narrative review is not reproducible, and relevant studies may be missing or selected with bias.
- **No primary data:** AEAM, the hypotheses and the questionnaire are proposed and unvalidated.
- **Context:** most experiments are U.S.-based and platform-specific; India-specific evidence is narrow and dated.
- **Time and measurement:** the largest experiments last weeks to months, and studies define exposure, polarization and echo chambers differently.
- **Platform involvement:** several key studies relied on platform data or staff, and one has published errata affecting Instagram metrics [23], [24].
- **Changing systems:** findings describe platforms as they were during data collection.
- **Sampling:** the proposed sample is purposive and would not generalise to a population.
- **Technical depth:** platform pipelines are proprietary, so the technical discussion is illustrative and not a description of any specific live system.

V. CONCLUSION AND FUTURE WORK

Personalization shapes what users see and can amplify some political content more than other content, yet its effects on attitudes and political knowledge are heterogeneous and depend on platform, outcome and direction of intervention. The more defensible conclusion is that exposure is uneven, largely invisible to users and moderated by interest and awareness, not that feeds uniformly trap users in bubbles. AEAM organises these findings into a testable chain and shows which links the evidence supports and which remain open. Because no data were collected, the contribution is conceptual, and every hypothesis remains untested.

Future work should run the proposed survey and experiment with Indian students across languages and regions, validate the questionnaire and test the equivalence of the simulated feed versions. Studies should cover short-video and messaging platforms, use longitudinal designs to test whether small effects accumulate through the feedback loop, and test whether gains in feed-evaluation skill persist beyond an immediate post-test. Independent platform audits and vetted researcher access would strengthen evidence on amplification, and conversational and generative-AI recommenders will need similar scrutiny.

APPENDIX A. PROPOSED QUESTIONNAIRE (UNADMINISTERED INSTRUMENT)

This instrument has **not** been administered. Before use it requires expert review, pilot testing, and assessment of reliability and validity. Rating items use 1 = strongly disagree to 5 = strongly agree.

A1. Eligibility and background. (1) Are you aged 18 to 25 and do you use social media, video or search platforms for news at least once a week? (Yes / No; "No" ends the survey.) (2) Age group: 18–20, 21–23, 24–25. (3) Field of study. (4) Main language(s) used for news. (5) Gender (optional). No identifying information is collected.

A2. Platform reliance. (1) Which platforms do you use for news? (select all) (2) Roughly what share of your news comes from feeds or recommended videos? (0–100%, steps of 10) (3) I usually encounter news through platform feeds or recommendations rather than by deliberately searching for it. (4) I often view political news or videos recommended by the platform. (5) A substantial proportion of the political news I consume comes from personalized feeds. *Scoring:* mean of the rating items and the percentage item rescaled to 1–5.

A3. Algorithmic awareness. (1) I know that my feed is selected and ordered by an algorithm. (2) I understand that my viewing, likes and follows influence what I am shown. (3) I know how to change settings that affect what is recommended to me. (4) Two people using the same platform can see very different political content. (5) I sometimes ask why a particular post or video was shown to me. *Scoring:* mean of five items.

A4. News-source use and perceived viewpoint diversity. (1) In a typical week, how many different news sources do you use? (0, 1–2, 3–4, 5–6, 7 or more) (2) I regularly read or watch sources that I expect to disagree with me. (3) I use news in more than one language or from more than one region. (4) I check a second source before sharing important news. (5) My feed shows me a wide range of viewpoints on public issues. *Scoring:* source diversity = mean of items 1–4 (item 1 rescaled to 1–5); item 5 is analysed separately as perceived viewpoint diversity.

A5. Political interest and participation. (1) I am interested in public affairs and current issues. (2) I follow news about government and politics closely. (3) I discuss public issues with friends, family or

classmates. (4) In the past 12 months, which have you done? (shared or commented on a political post; signed a petition; attended a meeting or protest; volunteered for a public cause; none) *Scoring:* interest = mean of items 1–3; participation = count of activities (0–4).

A6. Political knowledge (answer key in brackets). K1. Minimum voting age for Lok Sabha elections? (a) 16 (b) 18 (c) 21 (d) 25 [b]. K2. Which body conducts elections to Parliament and State Legislatures? (a) Supreme Court (b) Election Commission of India (c) Finance Commission (d) NITI Aayog [b]. K3. Which house of Parliament is directly elected? (a) Rajya Sabha (b) Lok Sabha (c) Both (d) Neither [b]. K4. Head of government at the Union level? (a) President (b) Chief Justice (c) Prime Minister (d) Speaker [c]. K5. Fundamental Rights are set out in which Part of the Constitution? (a) I (b) III (c) IV (d) V [b]. K6. Which law lets citizens request information from public authorities? (a) Right to Information Act, 2005 (b) Information Technology Act, 2000 (c) Consumer Protection Act (d) Companies Act [a]. K7. Normal term of the Lok Sabha? (a) 4 (b) 5 (c) 6 (d) 7 years [b]. K8. A way to challenge a law that violates Fundamental Rights? (a) Writ petition in the High Court or Supreme Court (b) Complaint to local police only (c) Petition to the Finance Commission (d) None of these [a]. *Scoring:* one point per correct answer (0–8); "Don't know" scores 0. Items must be checked for accuracy and currency before use.

A7. Scenario-based feed-evaluation task (pre-test and post-test). Participants view a researcher-created simulated feed of 12 fictional posts on a neutral topic, with no real parties or candidates; parallel Feeds A and B are used in counterbalanced order. They answer: (a) which three posts were most likely shown because of this user's past viewing, with a reason for each; (b) up to three viewpoints or sources that appear to be missing; (c) up to two actions the user could take to widen the feed. *Scoring (0–10):* (a) 0–3, one point per post correctly identified with a plausible reason; (b) 0–3, one point per valid missing viewpoint; (c) 0–4, up to two points per action (0 irrelevant, 1 vague, 2 specific and feasible). Two raters score independently and blind to condition; agreement (for example intraclass correlation) is reported.

A8. Perceived polarization (exploratory). (1) People with political views different from mine are hard to understand. (2) I feel that people in my country are deeply divided on public issues. (3) I feel uncomfortable discussing public issues with people who disagree with me. *Scoring:* mean of three items.

VI. DECLARATIONS

A. Funding

The author(s) received no financial support for the research, authorship and/or publication of this article.

B. Conflict of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

C. Data Availability

No primary datasets were generated or analysed. The proposed questionnaire is provided in Appendix A.

D. Ethics Statement

This paper is a literature review with a proposed research design. It did not involve human or animal subjects, and no ethical approval was required or sought for this paper. Any future empirical study will require approval from the institution's ethics committee.

E. Author Contributions

Mohit Chaudhari: Development of the conceptual framework, and writing – review and editing.

Ritesh Dyade: Conceptualization, writing – original draft, research methodology.

Vaibhav Babar: Literature review, preparation of the proposed research design.

F. Use of Generative AI

Generative AI assistance (Claude, developed by Anthropic) was used during manuscript preparation for drafting, editing, reference checking and formatting. The authors reviewed and approved the final text and take full responsibility for its content.

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VIII. REFERENCES

[1] T. Gillespie, "The relevance of algorithms," in Media Technologies: Essays on Communication, Materiality, and Society, T. Gillespie, P. J. Boczkowski, and K. A. Foot, Eds. Cambridge, MA, USA: MIT Press, 2014, pp. 167–194.

[2] E. Pariser, The Filter Bubble: What the Internet Is Hiding from You. New York, NY, USA: Penguin Press, 2011.

[3] C. R. Sunstein, #Republic: Divided Democracy in the Age of Social Media. Princeton, NJ, USA: Princeton Univ. Press, 2017.

[4] E. Bakshy, S. Messing, and L. A. Adamic, "Exposure to ideologically diverse news and opinion on Facebook," Science, vol. 348, no. 6239, pp. 1130–1132, 2015, doi: 10.1126/science.aaa1160.

[5] A. M. Guess et al., "How do social media feed algorithms affect attitudes and behavior in an election campaign?" Science, vol. 381, no. 6656, pp. 398–404, 2023, doi: 10.1126/science.abp9364.

[6] B. Nyhan et al., "Like-minded sources on Facebook are prevalent but not polarizing," Nature, vol. 620, no. 7972, pp. 137–144, 2023, doi: 10.1038/s41586-023-06297-w.

[7] G. Gauthier, R. Hodler, P. Widmer, and E. Zhuravskaya, "The political effects of X's feed algorithm," Nature, vol. 652, no. 8109, pp. 416–423, 2026, doi: 10.1038/s41586-026-10098-2.

[8] M. Eslami et al., "'I always assumed that I wasn't really that close to [her]': Reasoning about invisible algorithms in the news feed," in Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst. (CHI '15), 2015, pp. 153–162, doi: 10.1145/2702123.2702556.

[9] Z. Aneez, T. A. Neyazi, A. Kalogeropoulos, and R. K. Nielsen, "India digital news report," Reuters Inst. Study Journalism, Univ. Oxford, Oxford, U.K., 2019, doi: 10.60625/risj-qqd1-y198.

[10] D. Hartmann, S. M. Wang, L. Pohlmann, and B. Berendt, "A systematic review of echo chamber research: Comparative analysis of conceptualizations, operationalizations, and varying outcomes," J. Comput. Soc. Sci., vol. 8, no. 2, Art. no. 52, 2025, doi: 10.1007/s42001-025-00381-z.

[11] L. Terren and R. Borge, "Echo chambers on social media: A systematic review of the literature," Rev. Commun. Res., vol. 9, pp. 99–118, 2021, doi: 10.12840/ISSN.2255-4165.028.

[12] P. Covington, J. Adams, and E. Sargin, "Deep neural networks for YouTube recommendations," in Proc. 10th ACM Conf. Recommender Syst. (RecSys '16), Boston, MA, USA, 2016, pp. 191–198, doi: 10.1145/2959100.2959190.

[13] C. T. Nguyen, "Echo chambers and epistemic bubbles," Episteme, vol. 17, no. 2, pp. 141–161, 2020, doi: 10.1017/epi.2018.32.

[14] F. J. Zuiderveen Borgesius et al., "Should we worry about filter bubbles?" Internet Policy Rev., vol. 5, no. 1, 2016, doi: 10.14763/2016.1.401.

[15] F. Huszár, S. I. Ktena, C. O'Brien, L. Belli, A. Schlaikjer, and M. Hardt, "Algorithmic amplification of politics on Twitter," Proc. Natl. Acad. Sci. U.S.A., vol. 119, no. 1, Art. no. e2025334119, 2022, doi: 10.1073/pnas.2025334119.

[16] T. Bucher, "The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms," Inf. Commun. Soc., vol. 20, no. 1, pp. 30–44, 2017, doi: 10.1080/1369118X.2016.1154086.

[17] N. Helberger, "On the democratic role of news recommenders," Digit. Journal., vol. 7, no. 8, pp. 993–1012, 2019, doi: 10.1080/21670811.2019.1623700.

[18] S. Flaxman, S. Goel, and J. M. Rao, "Filter bubbles, echo chambers, and online news consumption," Public Opin. Q., vol. 80, no. S1, pp. 298–320, 2016, doi: 10.1093/poq/nfw006.

[19] E. Dubois and G. Blank, "The echo chamber is overstated: The moderating effect of political interest and diversity of media," Inf. Commun. Soc., vol. 21, no. 5, pp. 729–745, 2018, doi: 10.1080/1369118X.2018.1428656.

[20] S. González-Bailón et al., "Asymmetric ideological segregation in exposure to political news on Facebook," Science, vol. 381, no. 6656, pp. 392–398, 2023, doi: 10.1126/science.ade7138.

[21] C. A. Bail et al., "Exposure to opposing views on social media can increase political polarization," Proc. Natl. Acad. Sci. U.S.A., vol. 115, no. 37, pp. 9216–9221, 2018, doi: 10.1073/pnas.1804840115.

[22] R. Levy, "Social media, news consumption, and polarization: Evidence from a field experiment," Am. Econ. Rev., vol. 111, no. 3, pp. 831–870, 2021, doi: 10.1257/aer.20191777.

[23] "Erratum for the research article 'How do social media feed algorithms affect attitudes and behavior in an election campaign?' by A. M. Guess et al.," Science, vol. 386, no. 6726, Art. no. eadu8261, 2024, doi: 10.1126/science.adu8261.

[24] "Erratum for the research article 'How do social media feed algorithms affect attitudes and behavior in an election campaign?' by A. M. Guess et al.," Science, vol. 391, no. 6791, 2026, doi: 10.1126/science.aeh2575.

[25] R. Rani, H. Hendriana, M. G. Ristiana, and T. Loviana, "Gamified branching scenario innovation with Lumi Education: Transforming elementary school students' decision-making and science literacy," J. Primary Educ., vol. 15, no. 1, pp. 1–14, 2026, doi: 10.15294/jpe.v15i1.57383.

[26] W. Lin, J.-Y. Wang, and H.-P. Yueh, "Learning information ethical decision making with a simulation game," Front. Psychol., vol. 13, Art. no. 933298, 2022, doi: 10.3389/fpsyg.2022.933298.

[27] Y. Zheng et al., "Effects of digital game-based learning on students' digital etiquette literacy, learning motivations, and engagement," Heliyon, vol. 10, no. 1, Art. no. e23490, 2024, doi: 10.1016/j.heliyon.2023.e23490.

[28] S. Bai, K. F. Hew, and B. Huang, "Does gamification improve student learning outcome? Evidence from a meta-analysis and synthesis of qualitative data in educational contexts," Educ. Res. Rev., vol. 30, Art. no. 100322, 2020, doi: 10.1016/j.edurev.2020.100322.

[29] C. Dichev and D. Dicheva, "Gamifying education: What is known, what is believed and what remains uncertain: A critical review," Int. J. Educ. Technol. High. Educ., vol. 14, Art. no. 9, 2017, doi: 10.1186/s41239-017-0042-5.

[30] R. Smiderle, S. J. Rigo, L. B. Marques, J. A. P. de M. Coelho, and P. A. Jaques, "The impact of gamification on students' learning, engagement and behavior based on their personality traits," Smart Learn. Environ., vol. 7, Art. no. 3, 2020, doi: 10.1186/s40561-019-0098-x.

[31] C. Tanner, D. Schmocker, J. Katsarov, and M. Christen, "Educating moral sensitivity in business: An experimental study to evaluate the effectiveness of a serious moral game," Comput. Educ., vol. 178, Art. no. 104381, 2022, doi: 10.1016/j.compedu.2021.104381.

[32] E. O. Ibam, T. A. Adekunle, and O. C. Agbonifo, "A moral education learning system based on the Snakes and Ladders game," EAI Endorsed Trans. e-Learn., vol. 5, no. 17, Art. no. e3, 2018, doi: 10.4108/eai.25-9-2018.155641.

[33] Government of India, "The Digital Personal Data Protection Act, 2023," Ministry of Law and Justice, New Delhi, India, 2023.

[34] Ministry of Electronics and Information Technology, "Digital Personal Data Protection Rules, 2025," G.S.R. 846(E), The Gazette of India, Nov. 13, 2025.

[35] European Parliament and Council of the European Union, "Regulation (EU) 2022/2065 of 19 October 2022 on a single market for digital services and amending Directive 2000/31/EC (Digital Services Act)," Off. J. Eur. Union, vol. L 277, pp. 1–102, Oct. 2022. [Online]. Available: https://eur-lex.europa.eu/eli/reg/2022/2065/oj