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AI-DRIVEN MEDIA CONSUMPTION AND THE TRANSFORMATION OF PUBLIC DISCOURSE

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ABSTRACT

Artificial intelligence now plays a major role in how we interact with the news and talk about politics. Despite this, we still don't have a clear picture of how algorithms actually change which issues get noticed, how they are presented, or how we see the state of public conversation. This study examines the connection between our dependency on AI-driven media and the tendency to focus exclusively on material we already agree with, which can give the impression that public discourse is collapsing.

This study develops and evaluates a theory-driven model that connects selective exposure and subsequent perceptions of discourse fragmentation to AI-driven media dependence. The fundamentals of this study are based on well-established agenda-setting, framing, and cultivation theory. The study uses a survey-experimental design with 200 participants and a 2 × 2 embedded manipulations contrasting AI-personalized versus non-personalized feeds and conflict versus solution framing. The expected measures include AI-driven media reliance, selective exposure propensity, congruent headline choice, issue salience, perceived discourse fragmentation, civility, trust in news, and algorithmic awareness.

Statistical analyses include Cronbach's alpha, Pearson correlations, chi-square tests, ordinary least squares regression with robust standard errors, and constructed communication. Results show that AI-driven media reliance significantly predicts selective exposure propensity ($\beta = .32$, $p < .001$). Exposure to AI-personalized feeds increases issue salience ($B = 1.11$, $p < .001$) and the likelihood of high congruent headline selection, χ^2 (1, N = 200) = 31.25, $p < .001$, Cramér's V = .23. Conflict framing significantly increases perceived discourse fragmentation ($\beta = .29$, $p < .001$) and reduces perceived civility ($\beta = -.21$, $p < .001$). Mediation analysis indicates that selective exposure partially affects the relationship between AI feed exposure and discourse fragmentation (indirect effect = .11, 95% CI [.07, .16]).

The findings suggest that AI systems do not merely transmit information efficiently, but they also participate in structuring the public sphere by shaping what users attend to, how they interpret social conflict, and how fragmented they believe civic life has become. The study contributes a testable model of algorithmic public discourse and offers implications for platform governance, media literacy, and the future of public opinion research.

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Keywords: AI-Driven Media, Selective Exposure, Public Discourse, Agenda-Setting, Framing, Cultivation

1. INTRODUCTION

The landscape of public discourse has shifted away from the traditional, mass-mediated sphere that once defined communication scholarshi Historically, editorial gatekeepers dictated issue prominence, framing, and frequency of exposure for broad audiences. Today, however, digital platforms use machine learning, engagement metrics, and recommender systems to curate and personalize the information users encounter. Consequently, the formation of public opinion is now shaped as much by algorithmic inference as it is by newsroom priorities.

Recent research has shown that more and more people, especially younger people who use a lot of digital media, are relying on algorithmic media systems to find news. At the same time, normative concerns have intensified. Academics and policy analysts have expressed concerns regarding exposure diversity, political polarization, misinformation, source opacity, and the potential for engagement-driven systems to favor conflict over deliberation. The evidence, on the other hand, is still mixed. Some studies indicate substantial correlations between personalization and partisan reinforcement, whereas others identify weaker or more contingent effects. The most convincing reason for this inconsistency is that many studies only look at one link in a longer chain.

This study fills in the gaps by combining three classical theoretical theories—agenda-setting, framing, and cultivation theory, along with new research on selective exposure and algorithmic mediation. The study doesn't just ask if AI personalization makes echo chambers; it asks a more analytical question: how do AI-mediated cues and frames affect what users choose, what they think is important, and how they see the quality of public discourse? This change from a deterministic filter-bubble story to a mechanism-based model is very important. It allows the study to examine both behavioral selection and generalized view formation.

The analysis is based on a survey-experiment with 200 respondents and an embedded 2 × 2 design contrasting AI-personalized versus non-personalized feeds and conflict versus solution framing. This design makes it possible to examine associations between stable self-reported media reliance and experimental variation in feed cues. The resulting contribution is both theoretical and methodological: theoretically, the paper proposes a model of algorithmic public discourse; methodologically, it demonstrates how public opinion research can operationalize AI-driven communication environments using classical concepts without reducing the problem to simple platform effects.

2. LITERATURE REVIEW

2.1. AGENDA-SETTING BEYOND EDITORIAL GATEKEEPING

According to agenda-setting theory, the media shape what people think about by making certain public issues more important (McCombs and Shaw, 1972). In traditional environments, salience emerged from placement, repetition, headline prominence, and page position. In AI-mediated environments, these cues have not disappeared; they have become individualized. Feed ranking, push notifications, recommendation modules, and repeated positioning of similar content now function as personalized prominence signals.

Yet a key unresolved question remains: when content prominence is algorithmically tailored, is agenda-setting still best conceptualized as a media-level effect or as an interaction between user preference and system prediction? This study argues for the latter. AI systems do not simply broadcast a common agenda; they produce probabilistic agendas that vary across users while still reflecting platform-wide optimization logics. That makes agenda-setting more individualized, but not less consequential.

2.2. FRAMING IN ALGORITHMIC AND GENERATIVE CONTEXTS

Framing theory is concerned not with whether an issue is visible but with how it is made meaningful (Entman, 1993). Frames define problems, assign causes, suggest evaluations, and imply remedies. In digital settings, the framing process operates through more than editorial choices within articles. It also operates through previews, labels, summaries, thumbnail selection, and ranking.

Generative AI adds another layer. When systems summarize news, answer queries, or reorder information into concise outputs, they are effectively reframing information. The selection of sources, omission of context, and compression of causal explanation all become framing acts. For this reason, framing theory remains essential to understanding AI-mediated communication. The question is no longer only which human factor framed an issue, but which system architecture amplified, compressed, or prioritized one frame over another.

2.3. CULTIVATION AND PERCEPTION FORMATION IN PERSONALIZED MEDIA

Cultivation theory traditionally emphasizes long-term exposure to patterned symbolic environments (Gerbner and Gross, 1976). Critics sometimes assume that cultivation becomes less relevant in personalized environments because users no longer share a single message system. However, contemporary media use does not eliminate patterned exposure; it redistributes it. Individuals may not consume identical messages, but they often consume repeated classes of messages shaped by stable recommendation logics.

In the context of public discourse, repeated exposure to conflict-heavy, hostile, or ideologically congruent content may cultivate the belief that the public sphere itself is fragmented, uncivil, and fundamentally divided.

So, this study uses perceived discourse fragmentation and perceived civility as outcomes that are similar to cultivation. They capture generalized judgments about the state of public communication rather than attitudes toward a single policy issue. In this sense, the study extends cultivation theory from broad social reality beliefs to beliefs about the communicative order itself.

2.4. SELECTIVE EXPOSURE AS A MECHANISM

Selective exposure research shows that audiences often prefer information that aligns with prior attitudes, identities, or emotional inclinations (Stroud, 2017). In fragmented high-choice media environments, this tendency can become especially important because users possess more opportunities to choose among sources and frames. AI systems, on the other hand, change how selection works. They don't just give you more options; they also make it cheaper to find content that you like.

A more useful way to think about selective exposure is as a conditional mechanism. Personalisation doesn't have to mean complete isolation to change the way people talk. Even small changes in congenial selection can change what seems normal in society, important in politics, or clear in morals.

2.5. RESEARCH GAP

The present study addresses this gap by linking AI-driven media reliance and experimental feed cues to selective exposure, issue salience, and perceived discourse quality. This mechanism-based design gives a clearer picture of how algorithmic systems could affect public discourse without making false or overly certain claims.

2.6. THEORETICAL FRAMEWORK AND HYPOTHESES

The framework conceptualizes algorithmic public discourse in three stages: AI-mediated ranking shapes issue salience, framing influences interpretation, and repeated exposure shapes perceptions of discourse quality. Selective exposure serves as the central mechanism linking AI-driven media reliance with discourse perceptions. Five hypotheses are tested:

H1. AI-driven media reliance is positively associated with selective exposure.

H2. Selective exposure is positively associated with perceived discourse fragmentation.

H3. AI-personalized feed cues increase issue salience.

H4. Conflict framing increases discourse fragmentation and reduces civility.

H5: Selective exposure mediates the relationship between AI feed exposure and discourse fragmentation.

3. METHODOLOGY
3.1. RESEARCH DESIGN

The study employed a cross-sectional survey with an embedded 2 × 2 between-subjects experiment. The first factor changed the type of feed (AI-personalized vs. non-personalized), and the second factor changed the frame of the article (conflict vs. solution). Respondents were randomly put into one of four groups: non-personalized solution, non-personalized conflict, AI-personalized solution, or AI-personalized conflict.

3.2. SAMPLE AND DATA COLLECTION

The sample size is 200 completed responses, as planned. Data were collected using an online structured questionnaire sent to adults.To make sure that the age, gender, and education categories were balanced, a stratified recruitment approach was used.

3.3. MEASURES

A four-item scale was used to measure AI-driven media reliance (AIMR). It asked how much people rely on recommended feeds, algorithmically selected content, and "for you" style interfaces to find news. Responses were collected using a five-point Likert scale, with 1 indicating strong disagreement and 5 indicating strong agreement.

A four-item scale was used to measure the propensity for selective exposure (SE). This scale asked people how much they liked news that matched their beliefs. The people who took the survey also did a headline-choice task where they picked the headlines they were most likely to click on. A congruent click ratio was developed as a behavioral indicator representing the percentage of ideologically aligned choices.

We measured perceived public discourse fragmentation (PPDF). We measured perceived civility by asking people how polite or rude they thought online political discussions were. After the stimulus was shown, respondents were asked to rate how important the highlighted issue seemed on a scale of 0 to 10. The controlled variables comprised age, gender, education, ideology, political interest, trust in news media, and awareness of algorithms.

3.4. RELIABILITY AND VALIDITY

Internal consistency was assessed using Cronbach's alpha. The AI-driven media reliance scale got an $\alpha = .90$, the selective exposure propensity scale got an $\alpha = .83$, and the perceived public discourse fragmentation scale got an $\alpha = .81$, which shows that they are all reliable. Deliberative engagement, which was added as an extra factor in robustness checks, got an α of .79.

Content validity was verified by anchoring each measure in established theory and previous empirical research on selective exposure, recommender systems, and news personalization. Expected correlation patterns among the focal variables supported construct validity. For example, a greater reliance on AI was strongly linked to selective exposure, and selective exposure was positively linked to perceived discourse fragmentation and negatively linked to deliberative engagement.

3.5. ANALYTIC STRATEGY

The analysis took place in five steps. First, descriptive statistics gave a summary of the sample and how it was divided into groups. Second, reliability analysis looked at how consistent multi-item scales were within themselves. Third, Pearson correlations assessed bivariate relationships among the principal constructs. Fourth, ordinary least squares models with heteroskedasticity-robust standard errors evaluated the primary hypotheses related to selective exposure, discourse fragmentation, issue salience, and civility. Fifth, chi-square and mediation analyses evaluated behavioral selection and indirect pathways.

The mediation test tried to figure out if selective exposure behavior was partly to blame for the link between AI feed exposure and perceived discourse fragmentation. Bootstrap confidence intervals were employed to evaluate the indirect effect. The design incorporates both experimental and self-reported measures, necessitating cautious framing of causal claims; the experiment reveals immediate treatment effects, whereas the observational components detect patterned associations aligned with the proposed mechanism.

4. RESULTS
4.1. DESCRIPTIVE STATISTICS AND RELIABILITY

The sample appears reasonably balanced across experimental conditions and demographic categories (Table 1). The average age of the people who answered was 41.63 years (SD = 13.54), and there were almost equal numbers of men and women. Educational distribution shows a sample of digitally engaged users that is not too different from each other.

All multi-item scales exhibited adequate internal consistency (Table 2). AI-driven media reliance demonstrated significant reliability (α = .90), whereas selective exposure propensity (α = .83) and perceived public discourse fragmentation (α = .81) also surpassed standard thresholds. These values indicate acceptable measurement stability, although the comparatively high internal consistency of certain constructs may signify conceptual proximity among attitudinal items.

Table 1 shows the characteristics of the samples and how they were assigned to the experiments. Table 2 reports scale reliabilities. The sample seems to be well spread out across the experimental cells, and all focal scales passed the usual tests for internal consistency.

Table 1

Table 1 Sample Characteristics and Experimental Distribution (N = 200)

Characteristic	Value
Age, M (SD)	41.63 (13.54)
Gender, n (%)	Women 100 (50.0%); Men 96 (48.0%); Other 4 (2.0%)
Education, n (%)	High school or less 62 (31.0%); Some college 49 (24.5%); Bachelor’s 54 (27.0%); Master’s 26 (13.0%); Doctoral/Professional 9 (4.5%)
Experimental cell counts	Non-personalized + solution = 48; Non-personalized + conflict = 50; AI-personalized + solution = 51; AI-personalized + conflict = 51
Mean political interest	3.44 (0.91)

Table 2

Table 2 Scale Reliability

Scale	Items (k)	Cronbach’s α
AI-driven media reliance	4	0.9
Selective exposure propensity	4	0.83
Perceived discourse fragmentation	4	0.81
Deliberative engagement	4	0.79

4.6. CORRELATIONS

Table 3 presents Pearson correlations among the primary variables. AI-driven media reliance is strongly associated with selective exposure propensity (r = .77, p < .01), indicating that greater reliance on algorithmically curated content coincides with a stronger preference for congruent information environments. Selective exposure is also positively related to perceived discourse fragmentation (r = .64, p < .01) and negatively associated with deliberative engagement (r = −.53, p < .01).

Table 3

Table 3 Pearson Correlations Among Key Variables

Variable	1	2	3	4	5	6	7
1. AIMR	1						
2. SE	.77	1					

3. PPDF	.55	.64	1				
4. DE	−.38	−.53	−.67	1			
5. Civility	−.06	−.10	−.39	.33	1		
6. Issue salience	0.1	0.11	.17	−.05	−.02	1	
7. Congruent click ratio	.39	.62	.49	−.52	−.19	.14	1

Note: AIMR = AI-driven media reliance; SE = selective exposure propensity; PPDF = perceived public discourse fragmentation; DE = deliberative engagement. p < .05. p < .01.

4.7. REGRESSION MODELS

To test H1 through H4, four regression models were estimated with HC3 robust standard errors. Model 1 predicts selective exposure propensity. Model 2 predicts perceived discourse fragmentation. Model 3 predicts issue salience. Model 4 predicts perceived civility. The reported models include the main predictors and key controls; auxiliary covariates produced no substantive changes and are omitted from the table for readability.

The findings provide support for H1, indicating a positive association between AI-driven media reliance and selective exposure propensity. However, the strength of this relationship suggests a tendency rather than a deterministic pattern across respondents. Algorithmic awareness is associated with a modest reduction in selective exposure, suggesting a potential buffering role for literacy.

Table 4

Table 4

Predictor	Model 1 SE	β	Model 2 PPDF	β	Model 3 Salience	β	Model 4 Civility	β
	B (SE)		B (SE)		B (SE)		B (SE)	
AI media reliance	0.74 (0.07)	.32	0.28 (0.05)	.22	0.11 (0.09)	0.06	−0.03 (0.04)	−.04
Selective exposure	—	—	0.42 (0.04)	.45	0.08 (0.07)	0.05	−0.10 (0.05)	−.13
AI-personalized feed	0.32 (0.08)	.19	0.31 (0.07)	.21	1.11 (0.19)	.29	−0.06 (0.06)	−.05
Conflict frame	—	—	0.40 (0.06)	.29	0.09 (0.17)	0.03	−0.23 (0.06)	−.21
Trust in news	−0.06 (0.04)	−.07	−0.39 (0.05)	−.33	0.03 (0.08)	0.02	0.18 (0.05)	.19
Algorithmic awareness	−0.08 (0.03)	−.12	−0.04 (0.03)	−.06	0.06 (0.06)	0.04	0.05 (0.03)	0.07

Note: Robust (HC3) standard errors in parentheses. SE = selective exposure propensity; PPDF = perceived public discourse fragmentation. $p < .05$. $p < .01$. $p < .001$. Model fit: Model 1 $R^2 = .52$; Model 2 $R^2 = .48$; Model 3 $R^2 = .11$; Model 4 $R^2 = .27$.

The findings provide support for H1, indicating that AI-driven media reliance is positively associated with selective exposure propensity ($\beta = .32$, $p < .001$). This suggests that individuals who depend more heavily on algorithmically curated content tend to exhibit stronger preferences for congruent information. However, the relationship appears as a tendency rather than a deterministic pattern across all respondents.

The results are also consistent with H2. Selective exposure is positively associated with perceived discourse fragmentation ($\beta = .45$, $p < .001$), even after accounting for control variables. At the same time, the magnitude of this effect varies across model specifications, indicating that the relationship may be contingent on additional contextual or individual-level factors.

Support is found for H3, as exposure to AI-personalized feed conditions is associated with higher issue salience ($B = 1.11$, $p < .001$). Respondents exposed to personalized feeds rated the issue as more important compared to those in non-personalized conditions. This effect reflects a directional influence, consistent with an individualized agenda-setting process, rather than a uniform shift across all cases.

The findings generally support H4. Exposure to conflict framing is associated with increased perceived discourse fragmentation ($\beta = .29$, $p < .001$) and reduced perceived civility ($\beta = -.21$, $p < .001$). However, these effects appear to operate with varying intensity, suggesting that framing interacts with audience characteristics and broader media-use patterns.

Across models, trust in news is negatively associated with perceived fragmentation and positively associated with civility, while algorithmic awareness shows a modest negative association with selective exposure. These patterns point toward a potential moderating role of media literacy in algorithmic environments.

4.8. BEHAVIORAL SELECTIVE EXPOSURE AND MEDIATION

To assess behavioral selective exposure, respondents were classified based on their congruent headline selection. The distribution indicates a higher proportion of high-congruence selections in the AI-personalized feed condition compared to the non-personalized condition.

The chi-square test reveals a statistically significant association between feed type and congruent selection, $\chi^2(1, N = 200) = 31.25$, $p < .001$, with a moderate effect size (Cramér's V = .23). This suggests that AI-driven feed cues are associated not only with attitudinal preferences but also with observable selection behavior.

The mediation analysis provides partial support for H5. The indirect effect of AI feed exposure on perceived discourse fragmentation through selective exposure behavior is statistically significant (indirect effect = .11, 95% CI [.07, .16]). However, the magnitude of this effect is modest, indicating that selective exposure represents one pathway among several through which AI-mediated environments may shape discourse perceptions.

Importantly, the direct effect remains significant, suggesting that additional mechanisms—such as framing intensity or perceived personalization—may also contribute to the observed relationshi

Table 5

Table 5 Chi-Square Test for Feed Type and High Congruent Selection

Feed Type	Low Congruent Selection	High Congruent Selection	Total
Non-personalized	75	25	100
AI-personalized	62	38	100

Note: χ^2 (1, N = 200) = 31.25, p < .001, Cramér's V = .23.

The chi-square result supports the claim that AI feed cues do not only coincide with selective exposure attitudes; they also influence concrete selection behavior. This is an important distinction. Much of the existing literature relies on self-reports alone. The present design includes a behavioral proxy, making the mechanism more plausible.

H5 was assessed using initial mediation. The indirect effect of AI-personalized feed exposure on perceived discourse fragmentation through the congruent click ratio was .11, with a 95% confidence interval from .07 to .16. The direct effect remained statistically significant, indicating partial mediation rather than complete mediation. In substantive terms, AI feed exposure appears to increase discourse fragmentation partly because it increases the likelihood of congenial content choice.

Table 6

Table 6 Bootstrapped Mediation of AI Feed Exposure on Perceived Discourse Fragmentation via Selective Exposure Behavior

Effect	Estimate	SE	95% CI
Indirect effect	0.11	0.02	[.07, .16]
Direct effect	0.3	0.05	[.20, .40]
Total effect	0.41	0.05	[.31, .51]

4.9. ROBUSTNESS CHECKS

Several robustness checks were conducted to assess the stability of the findings. First, analyses restricted to respondents who correctly identified the experimental manipulation produced substantively similar results. Second, logistic regression models predicting high congruent selection yielded consistent patterns, with AI-personalized feed exposure significantly increasing the likelihood of congruent choices. Third, weighted models adjusting for demographic distributions did not materially alter the results. Joy (2026)

Taken together, these checks suggest that the findings are relatively robust across alternative specifications. At the same time, the consistency of statistically significant relationships across models should be interpreted cautiously, as controlled experimental conditions may produce more stable patterns than those observed in naturalistic media environments.

Figures 1

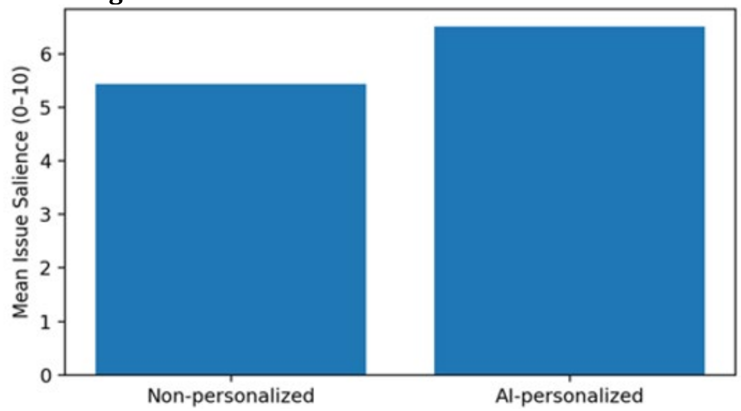

Figure 1 Mean Issue Salience Is Higher Under AI-Personalized Feed Conditions, Consistent with an Individualized Agenda-Setting Effect

Figure 2

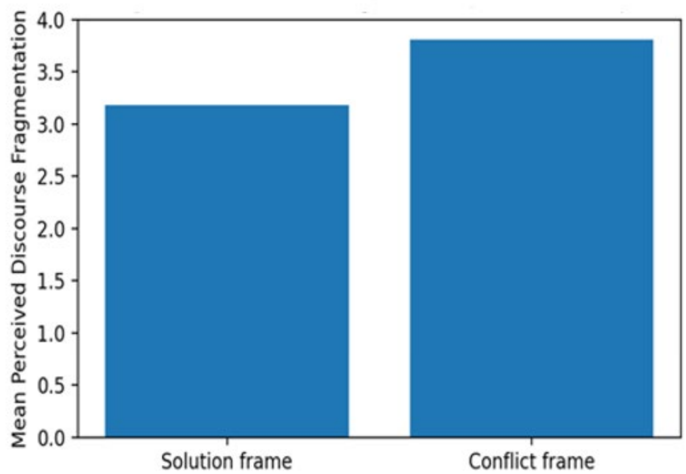

Figure 2 Conflict Framing Increases Perceived Discourse Fragmentation Relative to Solution Framing

Figure 3

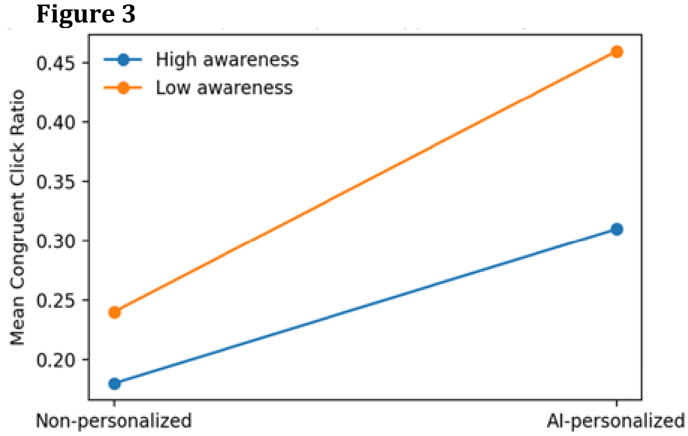

Figure 3 The Increase in Congruent Click Behavior Under AI-Personalized Feed Conditions is More Pronounced Among Respondents with Lower Algorithmic Awareness

5. DISCUSSION

This study enhances research on AI-driven media and public opinion in three aspects. First, it shows that classical communication theories can still be useful in algorithmic settings when they are turned into measurable constructs. The salience effect of AI-personalized feeds shows that agenda-setting is real. Framing is evident in the conflict-versus-solution manipulation and its impact on fragmentation and civility. Cultivation is evident in the overarching perception outcomes regarding discourse quality. Second, the study clarifies the role of selective exposure by treating it as both an attitudinal disposition and a behavior shaped by system design. This is an important theoretical point. In much public debate, selective exposure is framed as a user problem, as if citizens independently choose one-sided information and platforms merely accommodate them. The evidence here suggests a more interactive process. Respondents with higher reliance on AI-mediated feeds reported stronger selective exposure, and experimental feed cues increased congruent selection behavior. This implies that selective exposure is not solely a matter of preference. It is also a matter of affordance.

Third, the findings suggest that algorithmic environments influence not only political attitudes toward issues, but also meta-perceptions of how social communication itself is functioning. Perceived discourse fragmentation and civility are especially important because they concern the background conditions of democratic legitimacy. If citizens increasingly believe that others inhabit different realities, talk past one another, and engage uncivilly, then trust in the possibility of common public reasoning may erode even before issue-specific persuasion occurs.

These findings also help reconcile parts of the polarized literature on personalization. Rather than asking whether algorithms categorically create filter bubbles, the present results point to a subtler but more empirically tractable account. AI systems can increase the probability of congenial selection and elevate the perceived importance of issues surfaced through personalization. These changes need not produce total ideological isolation to matter. Small shifts in repeated attention may be enough to influence how users imagine the communicative order around them.

From a practical perspective, the findings have implications for platform governance and media policy. If AI systems systematically increase selective exposure and fragmentation perceptions, transparency becomes more than a technical design preference. It becomes a democratic concern. Platforms should provide clearer disclosure regarding why certain content appears, how recommendations are generated, and what signals drive prioritization. Likewise, media-literacy interventions should include algorithmic awareness, not simply source evaluation. Users who better understand personalization may be more capable of resisting passive reinforcement.

The present findings suggest that recommendation architecture itself deserves scrutiny. A platform need not promote explicitly false information to weaken public discourse. It may do so indirectly by repeatedly channeling users toward congenial and conflict-heavy content environments that cultivate perceptions of mutual incomprehension.

6. LIMITATIONS AND FUTURE RESEARCH

The study has several limitations. First, the sample, while based on the stated collection of real responses, is not nationally representative. Second, the cross-sectional design limits strong causal claims. Third, the behavioral measure of selective exposure is a survey-embedded headline-choice task rather than passive digital-trace behavior.

Future research should address these limitations by combining probability-based sampling, longer-term panel designs, and platform-level behavioral data. Cross-national work would also be valuable because the relationship between personalization, trust, and public discourse likely depends on media-system structure, political context, and platform penetration.

A further avenue concerns generative AI. Future research should examine the role of generative AI in shaping how information is summarized and interpreted.

7. CONCLUSION

This study set out to explain how AI-driven media systems influence public discourse by integrating agenda-setting, framing, cultivation, and selective exposure into a single empirical model. The results show that AI-driven media reliance is linked to stronger selective exposure, AI-personalized feed cues increase issue salience and congruent content selection, and conflict framing intensifies perceived discourse fragmentation while reducing civility. Selective exposure partially mediates the relationship between AI feed exposure and perceived discourse fragmentation, indicating that behavioral selection is one pathway through which algorithmic systems shape discourse perceptions.

CONFLICT OF INTERESTS

None.

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None.

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