Mainstreaming revisited: Effects of media proliferation on partisan opinion dynamics

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Abstract

The early 21st century has seen heightened political polarization in the U.S., with some scholars attributing the widening partisan divide to the proliferation of media choices. We evaluate this high-choice media hypothesis by employing an agent-based model that lets us integrate active audience and interpersonal communication theories into cultivation theory. Our model is based on social influence and homophily mechanisms, with baseline parameters capturing the formation of two polarized opinion communities. We investigate media effects by incorporating two facets of media evolution into the model: the proliferation of mass media systems and shifts in audience reach. Agents possess the autonomy to follow or unfollow mass media sources when multiple ones coexist. Although agents can actively select media outlets aligned with their beliefs, which fosters competition among media for a limited audience, the results underscore the persistent mainstreaming effects of mass media. By simulating media effects as a systemic force, our model challenges the assumption that a high-choice media environment exacerbates polarization in the age of social media.

Keywords: Agent-based modeling, polarization, mainstreaming, media effects, cultivation, selective exposure

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Investigations into the relationships between high-choice media environments and political polarization have garnered significant research attention. Multiple systematic literature reviews have either specifically focused on media's role in polarization or have included relevant sections on media while examining other facets of political polarization (Farrell, 2012; Haidt & Bail, 2022; Iyengar et al., 2019; Jost et al., 2022; Kubin & von Sikorski, 2021; Pierson & Schickler, 2020; Prior, 2013; Tucker et al., 2018; Zhuravskaya et al., 2020). This literature reports mixed evidence about whether the high-choice media environment should be held responsible for the current polarized political climate.

Diverse explanations are offered for such mixed evidence, including the lack of consensus on what constitutes "media," the challenge of disentangling the effects of media from other factors, and different methodological approaches, such as observational research versus self-report. Another reason is that scholars still tend to conceptualize media as exerting impact from a local and individualized context rather than as a systemic force (Lang, 2013; Sherry, 2015). In this reductive and linear effects perspective, we often expect direct interactions with specific media content to result in immediate changes. However, decades of experimental research have shown that such effects are small (Bennett & Iyengar, 2008). A simplistic view of media effects limits our understanding of their role within our complex and interconnected media environment.

Let us use the example of the journey of a single tweet to demonstrate how a piece of content might make an impact within today's media landscape. The tweet, potentially originating from a passionate conspiracy theorist, might be re-posted by a highly partisan news platform, illustrating the concept of networked agenda-setting. It then experiences a surge of retweets on Twitter, from a mix of influencers, various mainstream media outlets, regular users, and possibly social bots, exemplifying the ideas of multi-step information flows and the mediation opinion leaders. Imagine you, a politically active person from a rival party, encounters this tweet. The tweet appears in your WhatsApp family group, shared by a distant relative, a case of incidental exposure, or the "news-finds-me" phenomenon. Opting to stay quiet to avoid conflict with many relatives who share these views, you may demonstrate the spiral of silence effect. Yet, this encounter solidifies your belief in the "delusional" nature of the opposing side, a result of confirmation bias and attitude reinforcement. Such a belief is further strengthened by frequent and similar experiences in the past, indicative of a cultivation process.

When we adhere to the traditional understanding of media effects, focusing solely on the impact of this one tweet in isolated contexts, it becomes challenging to estimate the effect size or summarize the mechanisms with a single theory. Moreover, the measurable effects of such an encounter are not easily discernible, as they may not lead to immediate changes in attitudes or opinions. Instead, they often serve to reinforce existing attitudes. This complex interplay between multiple mechanisms and the absence of observable immediate changes highlights the limitations of our traditional understanding of media effects, especially when it comes to capturing the intricate dynamics of political polarization in the current information ecology.

Agent-based modeling (ABM) offers a way to tackle such complexity. ABM is a computational technique that simulates the interactions of individual entities, known as "agents," within an environment (Helbing, 2012; Macal & North, 2005). Agents are designed with unique characteristics, behaviors, and decision-making processes modeled by rules and algorithms. Agent heterogeneity and autonomy can also be accounted for. Through iterative updates, ABM simulates the evolving states, behaviors, and interactions among agents over time. ABM lets us examine how individual-level actions shape the emergence of system-level patterns and non-linear dynamics, such as feedback loops that may remain hidden when analyzing the system at an aggregate level (Bankes, 2002; Helbing, 2012). Agent-based modeling has gained popularity in social sciences since the 1990s (Axelrod, 1997; Epstein & Axtell, 1996; Gilbert & Doran, 1994). It recently has attracted attention from communication scholars due to its efficacy in formalizing and integrating theories at multiple levels (Waldherr et al., 2021).

The study of public opinion formation, as an emergent phenomenon arising from complex interactions among individual agents, aligns well with the capabilities of ABM. Previous research, primarily in statistical physics and quantitative sociology, has a history of using ABM to explore opinion dynamics (for a comprehensive review, see Castellano et al., 2009), including opinion polarization (Levin et al., 2021). However, the role of media has only recently gained attention within opinion models (e.g., Hu & Zhu, 2017; Tokita et al., 2021).

In this study, we have developed a minimalist agent-based model that examines effects of the changing media systems on political polarization. Building upon Sasahara et al. (2021), our model incorporates two fundamental mechanisms: social influence and homophily. These mechanisms capture the forces that drive the formation of partisan echo chambers, a phenomenon observed in real-world data (e.g., Conover et al., 2011). Our key innovation is to add mass media as an additional source of influence in the social media environment. The model aims to contribute to the formal theory-building of mass media effects, specifically the idea of mainstreaming proposed by cultivation theory (Gerbner et al., 1980, 1982). ABM lets us create a virtual laboratory where we can also examine competing theories, such as selective exposure and the effects of interpersonal influence. Finally, while previous research on mainstreaming has often relied on cross-sectional survey data, ABM allows for the exploration of potential temporal dynamics in the mainstreaming process.

Cultivation theory in the age of active media consumption

Cultivation theory hypothesizes that narratives that share similar outlooks and ideologies in mass media have cumulative effects on viewers over time (Morgan et al., 2015). Unlike many "middle-range" media theories that operate within a specific domain or context (e.g., agenda setting for news), cultivation theory was originally proposed to cover long term effects of entire media experiences (Gerbner & Gross, 1976). The scope of analysis was based on a broader research program known as the Cultural Indicators Project, which aimed to explore shared collective experiences in media and their impacts.Seeing the media landscape as a holistic system, the program started with large-scale content analysis that used systematic sampling to demonstrate the salient themes of the entire television landscape (Gerbner, 1969). Over the last five decades, the message system analysis alone has shown patterns of TV representations of controversial topics including violence, women's rights, and homosexuality (Morgan & Shanahan, 2010; Signorielli et al., 2019).

Emerged in the 1960s, Cultural Indicators Project went beyond content analysis and turned to the effects of television on society and individuals, as a response to television becoming a dominant medium of communication. This line of research gave the birth to cultivation theory. Based on the results of message system analysis, cultivation research looks for evidence of correlations between patterns of TV content and perceived social reality and attitudes.

One key aspect of cultivation theory is the concept of "mainstreaming," which suggests that television viewing can lead to the formation of shared attitudes and beliefs among heavy viewers. Research consistently shows that heavy television viewers, regardless of demographic characteristics or political affiliations, tend to hold more similar political attitudes on contentious issues such as racial segregation, homosexuality, and abortion (Gerbner et al., 1980, 1982). For instance, Gerbner et al. (1982) found that heavy-viewing liberals, who generally manifest less opposition to abortion, exhibited stronger anti-abortion views compared to light-viewing liberals. The difference in attitudes between liberals and conservatives on this issue was 23 percentage points among light viewers but reduced to just 7 points among heavy viewers (Gerbner et al., 1982). This demonstrates how television's mainstreaming effect moderates partisan polarization narrowing the divergence in attitudes between different political groups.

Over the years, cultivation theory has been refined and expanded upon by various scholars and researchers. A recent meta-analysis of cultivation research has shown that television has a stable and modest effect on attitudes towards various cultural issues (Hermann et al., 2021). Cultivation theory has also been applied to different media contexts, such as news media and social media (Morgan et al., 2015).

Cultivation theory, despite its significant influence, has faced various challenges and criticisms (Chaffee & Metzger, 2001; Katz & Fialkoff, 2017; Potter, 2014). First, the theory was developed when television dominated the media landscape and viewers had limited options. Critics argue that cable TV, streaming platforms, online content, and search engines have provided audiences with access to a wide range of media sources, challenging the assumption of media content homogeneity and the impact of television as the dominant medium. In other words, each mass media channel would have limited audience reach. We refer to this criticism as the "audience fragmentation" argument hereafter. Second, critics argue that the theory neglects the active role of audiences in selecting and seeking out media content that aligns with their existing beliefs and attitudes. With the rise of the internet and social media, individuals have greater agency in choosing the information they consume, potentially leading to the formation of echo chambers. We refer to this as the "active audience" argument. Critics also highlight the importance of interpersonal interactions, opinion leaders, and cultural background in shaping media effects, which are not adequately addressed in the theory.

Morgan et al. (2015) have provided conceptual rebuttals to these criticisms. In response to the audience fragmentation argument, the extent of information diversity to which mass media users are exposed remains a topic of debate. While users have access to a wide range of information in theory, the actual fragmentation of information may still be consistent with the traditional 80/20 rule, according to which the majority of information consumed by people originates from a few top sources (Huang & Wang, 2014; Smyrnaios et al., 2010). Research conducted by Webster and Ksiazek (2012) and more recently Yang et al. (2020) shows that even though individual mass media channels have limited audience, the collection of legacy and mainstream media still dominates online traffic. Moreover, studies on partisan media diets challenge the notion of strong selective exposure or echo chambers, finding a moderate level of cross-cutting exposure between Democrats and Republicans when it comes to news sources (Guess, 2021; Lelkes & Westwood, 2017; Nyhan et al., 2023).

Regarding the active audience argument, while the emergence of new technologies has fostered a participatory culture that emphasizes the active engagement of viewers, having more media choices does not necessarily invalidate the assumption of media content homogeneity and the existence of accumulated media effects (Chaffee & Metzger, 2001). In practice, various societal and technological forces, such as ranking algorithms and advertising, shape the prioritization and delivery of content to us (Fortunato et al., 2006). Despite being active in their media consumption, audiences in the current age can still actively select but subscribe to a mono-culture of positions and ideas (Bakshy et al., 2015).

Connections between theories and model

Based on the debate surrounding mass media effects and the challenges to cultivation theory, we propose the following hypotheses:

H1: Mainstreaming hypothesis. The presence of a centralized media system ($n = 1$) homogenizes opinions, contingent upon the media's audience reach, in comparison to the absence of media ($n = 0$).

H2: Proliferation-diversification hypothesis. Increasing the number of media systems ($n \geq 2$) diversifies opinions, depending on the audience reach of the media systems.

These two hypotheses reflect the mainstreaming effect proposed by cultivation theory and how the proliferation of mass media systems might weaken it. In the next subsection, we highlight the theoretical underpinning within and beyond cultivation that informed the design of our model, addressing the specific challenges to cultivation theory.

Following the content homogeneity conjecture in cultivation theory (Morgan & Shanahan, 2010), we make the simplifying assumption that all media systems adhere to a similar content creation logic. That is, the messages produced by a media system reflect the average value of the opinions held by its audience at the current time. Therefore, media systems in the current study are defined as feedback loops of audience opinions. This design addresses a cultivation theory criticism according to which media content is not created in isolation, but rather influenced by a feedback loop with public opinion. The choice of averaging opinion values among the audience acknowledges that media producers and creators often strive to adopt a middle ground to avoid controversies and appeal to a wider audience.

When multiple media systems exist, each caters to its own set of subscribers. As a result, the audience members are split among different media systems in our model. This division of audience leads to the diversification of media messages to a certain extent, as each media system becomes responsible for delivering content that aligns with the preferences and interests of its specific subscriber base. This diversification of media messages reflects the varying perspectives and ideologies present within different media systems, providing audiences with a range of viewpoints and opinions to consider.

Another consideration in our modeling design is the tolerance level of the audience towards the values expressed in the media messages. Audience opinions will be influenced only by messages that align with their tolerance levels. This modeling approach captures the selective exposure process at the message level, where individuals are more likely to engage with and be influenced by content within their tolerance range.

When there are multiple media systems, the audience can also switch from one media system to another. This models the selective exposure process at the source level, as individuals actively choose different media sources based on their preferences and interests. Overall, each audience member plays an active role in determining its media exposure and shaping its information environment within the model.

The current study builds directly upon the framework established by Sasahara et al. (2021), which models the concept of asynchronous interpersonal communication and following/unfollowing as observed in social media platforms. Their design requires an active agent to consider all messages in its feed that are within its tolerance level. Our model adds messages originating from mass media sources.

In sum, while the primary objective of the current study is to model the mainstreaming effects described in cultivation theory, we also incorporate insights from other media effects theories, such as selective exposure (Sears & Freedman, 1967), two-step flows (Katz, 1957), the feedback-loop of communication (Trilling, 2022), and the reinforcement of mass media effects through interpersonal communication (Slater, 2007). By embracing these seemingly contradictory theories, the model strives to provide a holistic and systemic understanding of the complex dynamics between media, interpersonal communication, and opinion formation. The subsequent section will provide a detailed outline of the model specification.

Model design

Baseline model

Population and network. The model is initialized with a directed random graph that connects N agents (i.e., nodes) through E links, where a link from i to j means that agent i follows agent j. The minimum out-degree for each agent is set to one, i.e., each agent follows at least one other agent.

Opinion update rule. Every agent i is initialized with an opinion o_i, sampled from a uniform distribution ranging from $[-1, 1]$, a tolerance level ϵ, and social influence strength μ (population-wide parameters). At each time step $t > 0$, a randomly selected active agent i checks its social media feed. The feed consists of the messages $M_i(t)$ posted by friends followed by i. At most l_i messages can be displayed. The limited screen size l_i is randomly assigned at the start and does not change thereafter.[1] If there are any messages on the screen, the agent updates its opinion $o_i(t)$ by combining three components: (A) the previous opinion $o_i(t-1)$; (B) the average of a set of opinions expressed in compatible messages on its social media screen (social influence); and (C) random noise ρ_0. This is implemented by the following equation:

$$o_i(t) = o_i(t-1) + \mu \frac{\sum_{m \in M_i(t-1)} I(m, o_i(t-1))m}{\sum_{m \in M_i(t-1)} I(m, o_i(t-1))} + \rho_0 \tag{1}$$

where the function I determines the compatibility between a message from the screen and the agent's existing opinion:

$$I(m, o_i(t)) = \begin{cases} 1 & \text{if } |o_i(t) - m| < \epsilon \\ 0 & \text{if } |o_i(t) - m| \geq \epsilon. \end{cases} \tag{2}$$

Posting and reposting behaviors. At each time step t, the active agent i also exhibits posting or reposting behavior. There is a probability p that the agent posts an original message $m_i(t) = o_i(t)$, representing its current opinion. Conversely, with probability $1 - p$, the agent reposts a randomly selected compatible message from its social media feed $M_i(t)$.

Following and unfollowing behaviors. The agent's third activity involves following and unfollowing behaviors. With a probability q, agent i may choose to unfollow one of its friends who posted or reposted an incompatible message from $M_i(t)$, and simultaneously follow a new friend. To acquire a

[1] Screen size is conceptually analogous to the idea of heavy versus light viewers in cultivation theory. However, individual differences are not the focus of the current study, so we do not explore the effect of the screen size parameter.

new friend, the agent selects the original poster of a random compatible (re)post from its screen. If such a poster exists and is not already followed by the agent, the agent follows this new friend. If there are no compatible messages available or if the chosen poster is already followed, agent i seeks a recommendation from the system. The system provides a list of l_i agents who recently (re)posted compatible messages. Agent i then follows a random agent from the recommended list, if the chosen agent is not already followed. If neither following a new compatible original poster nor a recommended agent results in a new connection, agent i randomly follows an agent who is not currently followed.

Modifications from Sasahara et al. (2021). While this baseline model takes direct inspiration from Sasahara et al. (2021), there are notable differences. The first difference is the inclusion of noise ρ_0 in opinion updates. This makes the distribution of opinions continuous rather than discrete, with clusters in case of polarization or fragmentation of opinions. The second difference is that the three methods of establishing new friendships (repost, recommend, and random) are not treated as experimental conditions but rather as a hybrid process that emulates real social media user behaviors. As Sasahara et al. (2021) modeled, personal preference and algorithmic recommendation both tend to reinforce homophily, but they only accelerate the polarization process and do not change the number of opinion communities in the final state. Similarly, the social influence strength parameter μ solely affects the speed of opinion formation (as long as $\mu > 0$). The ultimate determinant of the final number of opinion communities remains the level of tolerance ϵ exhibited by the agents.

Summary. Overall, the baseline model simulates a social media world where agents share opinions of their own and others, change their opinions through social influence, and change the network structure through homophilic following and unfollowing. Based on explorations with the baseline model, we fix the aforementioned parameters as shown in Table 1.

Mass media systems

A mass media system is defined here as a special agent (network node). It averages the opinion values of its followers (audience) and sends it back to them, working as a feedback loop. In this design, a specific mass media system labeled as j has a probability s to disseminate a message $m_j(t)$ (average opinion) to its audience $a_j(t)$ at time step t. Otherwise, with probability $1 - s$, j does not produce any message. Mathematically, the media message is computed as the mean of the opinions held by the audience:

$$m_j(t) = \frac{\sum_{i \in a_j(t)} o_i(t)}{|a_j(t)|} + \rho_1 \tag{3}$$

where $o_i(t)$ represents the opinion of individual audience member i at time t. To incorporate variation, a random noise ρ_1 is also added.

Effects of media messages. When incorporating media influence, agents update their opinions following the same logic of social influence, considering only the media messages that they find compatible with their own opinions. This is how the model design incorporates *selective exposure* at the message level. Equation 1 is updated as follows:

$$o_i(t) = o_i(t-1) + \mu \frac{\sum_{m \in \bar{M}_i(t-1)} I(m, o_i(t-1))m}{\sum_{m \in \bar{M}_i(t-1)} I(m, o_i(t-1))} + \rho_0. \tag{4}$$

Here, $\bar{M}_i(t-1)$ includes messages generated by both friends and media systems that agent i follows at the previous time step.

Experimental setup. Two parameters are of interest to explore the proposed hypotheses: the total number of media n and the total audience reach denoted as $|A|$. In the current design, $A = \cup_j a_j$ is the total audience of all media systems and remains constant. To investigate the mainstreaming hypothesis, a single mass media system ($n = 1$) is added to the baseline model, and the audience reach (A) is manipulated from low to high (i.e., between 10% and 90% of the agent population). The dynamics of opinion formation are compared against the baseline model to assess the impact of the mass media. To explore the proliferation-diversification hypothesis, the number of media systems is varied from $n = 2$ up to a maximum of $n = 5$.

Audience fragmentation. While the number of media systems n increases linearly, it is important to highlight the dynamics that are specifically present in conditions where $n > 1$. When $n > 1$, the model creates audience fragmentation: the total audience reach $|A|$ must be divided among the multiple media systems. In the current design, the audience reach is initially and randomly divided into n non-overlapping shares, so that $|A| = \sum_j |a_j|$.[2] Let's consider a scenario where the audience reach is 90% and there are $n = 3$ media systems. As a result of the random split, 10% may follow media system *A*, 55% may follow

[2] We experimented with allowing overlap, where one agent can follow multiple media sources, but the differences in terms of their influence on opinion dynamics were found to be trivial.

B, and 25% may follow *C* ($10\% + 55\% + 25\% = 90\%$).

Source selection. While the audience is initially split into different shares, individual agents can choose to unfollow one media system and follow another based on the same logic of homophily between agents. When an active agent i engages in following and unfollowing behaviors, the agent may choose to unfollow a media system that it currently follows but posts an incompatible message, and *simultaneously* follow a new media system. The agent follows the same priority criteria as for following new agents, with the distinction that the search process specifically looks for media systems. That is, the agent first examines the original posters of compatible reposts on their screen. If there is at least one original poster that is a media system and has sent out a compatible message, and the agent does not already follow that media system, the agent follows this new media system. If there are no original posters that are media systems or if the chosen media system is already followed, the agent seeks recommendations from the system. The system provides a list of $l_i \times 3$ original posters who have recently sent out compatible messages and who are not followed by the agent. From this recommended list, the agent randomly selects and follows one that is a media system. If neither following a new compatible original poster that is a media system nor following a recommended media system results in a new connection, the active agent randomly follows a new media system that is not currently followed. This process reflects the phenomenon of source-level *selective exposure*, whereby agents tend to follow media systems that are compatible with their own opinions. As a result, the distribution of audience shares for each media system can vary throughout the simulation, allowing for dynamic shifts in the popularity of different media systems.

Measures

Opinion heterogeneity. We employ the concept of entropy to assess the heterogeneity of the opinion space. In practice, the entropy of the opinion space is computed by discretizing the opinion variable into 100 bins:

$$H(t) = -\sum_{o \in O(t)} f(o) \log(f(o))\, do \tag{5}$$

where $O(t)$ is the set of opinion bins at time t and $f(o)$ is the number of agents who have opinions in bin o. Higher entropy values indicate greater heterogeneity in the opinion space, reflecting a more diverse range of opinions.

Opinion clusters. We employed Gaussian Mixture Models (GMMs) with Maximum Likelihood Estimation (MLE) to assess the number of discrete clusters of opinion spaces. GMMs are a machine learning technique to classify complex probability distributions. They are particularly useful for modeling data that is believed to be generated from a mixture of normal distributions, as we assume the opinions are in the current study given the random noise ρ_0 in their generation. The idea behind GMMs is to approximate the underlying distribution by representing it as a weighted sum of several Gaussian distributions. In the current study, each Gaussian component in the mixture model represents a cluster of opinions. To determine the optimal number n_{GMM} of components or opinion clusters, an algorithm iterates from one up to a maximum of 10 clusters. For each number of clusters, the algorithm computes the Akaike Information Criterion (AIC) value. The AIC is a statistical measure that quantifies the trade-off between model complexity and goodness-of-fit. The lowest AIC value determines the optimal (most likely) n_{GMM}. Based on the GMM output, each agent is assigned to an opinion cluster. We then examine the links within and between opinion clusters to determine whether these clusters correspond to separate network communities.

Simulation configuration

In theory, we can have any number n of media systems—zero or more. The audience reach $|A|$ is a bounded continuous variable, which ranges from 0% to 100% of the population. To simplify the simulation, we use $1 \leq n \leq 5$ and $|A| \in \{10\%, 30\%, 50\%, 70\%, 90\%\}$. This results in a total of 25 pairs of parameter configurations of interest, plus the baseline model.

For each configuration of parameters, we run 100 simulations of the model to obtain reliable statistical results. For each simulation, we run a total of 10^4 time steps to capture the dynamics.

Results

Baseline model

The baseline model (i.e., $n = 0$ mass media systems) typically leads to a polarized opinion space characterized by the presence of two distinct opinion communities, consistent with prior experiments using tolerance level $\epsilon = 0.5$ Sasahara et al., 2021. This opinion evolution is mirrored in the network structure, as the agents tend to form two distinctive network communities in the end. Figure 1 provides an example illustrating the dynamics. However, these dynamics are not deterministic: over 100 runs of the simulation, approximately 72% resulted in polarized opinions while in the remaining 28% of the runs, the opinions converged to a single cluster. The presence of stochasticity in the model can be attributed to the introduction of random noise in the opinion updates.

Mainstreaming effects

H1 posits that the presence of one mass media system will "homogenize" the opinion space. Our analysis reveals that in the presence of one mass media system with a high audience reach (90%), the opinions tend to converge towards a centered mainstream group with a mean value around zero, accompanied by two marginal groups at the extremes, as illustrated in Figure 2. While we observe three distinct opinion clusters, the final network structure does not exhibit three distinct communities.

We measure opinion entropy to quantify the effects of mass media systems on opinion heterogeneity. Figure 3A shows that the presence of a single media system leads to a decrease in opinion heterogeneity. While the baseline model also tends to reduce the entropy, the inclusion of a single mass media system leads to a faster decrease. The homogenizing effects are contingent upon audience reach: Figure 3B shows that when the mass media system's audience is below 10%, no effect is observed. Between 10–30%, higher mass media audience reach corresponds to lower entropy. Beyond, 30%, a larger reach primarily accelerates the decrease in entropy (Figure 3A).

The Gaussian mixture model analysis shows that the distributions of final opinions can be classified into three distinct types (Figure 4A–C): homogenization, polarization, and mainstreaming.[3] When GMM identifies a single cluster as optimal ($n_{GMM} = 1$), the final opinion distribution is normal (Figure 4A). When $n_{GMM} = 2$, the final opinion distribution is bimodal (4B). When $n_{GMM} > 2$, the final opinion distribution tends to become multimodal, characterized by a mainstream opinion group in the middle and two marginal groups occupying the extremes (Figure 4C). While we are focusing on the case of a single mass media system here, these three classes of final opinion distributions are observed irrespective of the number of mass media.

Figure 4D shows that as the audience reach of mass media increases, the probability of forming polarized opinion distributions decreases: the likelihood of polarization (defined as the fraction of simulations leading to this outcome) decreases from 72% in the baseline model to 5% when the mass

[3] We use the term "mainstreaming" here solely to refer to a specific type of opinion distribution; it does not suggest that the original mainstreaming survey data (e.g., Gerbner et al., 1982) were also characterized by multimodal distributions.

media system has a 90% audience reach. Conversely, the likelihood of mainstreaming increases monotonically with audience reach, from 7% in the baseline model to 95% when the mass media system has 90% audience reach. The likelihood of forming homogenized opinions initially increases from 21% in the baseline model to 30% when the media system has 10% audience reach; it eventually decreases to zero as the audience reach continues to increase.

Both entropy and GMM analyses support H1, demonstrating that the presence of a single mass media system leads to more homogeneous opinions. These two measures offer complementary insights into the evolution of opinions. The entropy analysis shows that the converging effects are conditional on audience reach, occurring primarily between 10% and 30% audience reach. The GMM analysis identifies the specific type of convergence induced by the presence of a single high-reach media system, with the dominant pattern being a transformation toward a mainstream opinion group. These insights become more meaningful when considering cases with more than one mass media system, explored next.

Proliferation-diversification

H2 posits that as the mass media systems proliferate, the opinions diversify. Let's first consider the effects of increasing the number of mass media systems when they have a fixed total audience reach of 90%. Figure 3C shows that media proliferation has a non-linear effect on the final opinion diversity, as further illustrated by the U-shaped entropy trend in Figure 3D. Compared to the baseline model (no mass media), the presence of one to four mass media systems leads to less diverse final opinions, indicated by lower average entropy. Opinions with two media systems have the lowest diversity. When five media systems are included, the final opinions become slightly more heterogeneous than in the baseline, on average. These effects are not statistically significant ($p > .05$ for all pairs), indicating a minimal effect size.

Upon closer examination of scenarios with different numbers of media systems ($1 \leq n \leq 5$) and a consistent total audience reach of 90%, we note several patterns in the types of final opinion distributions, as illustrated in Figure 4E. The likelihood of observing the homogenization pattern increases from zero ($n = 1$) to around 65% of the simulations ($n \geq 3$). The likelihood of polarization increases to around 30% with two or more media systems. Finally, the likelihood of mainstreaming decreases rapidly from dominating (93% for $n = 1$) to less than 5% ($n \geq 3$). With more than two mass media systems, we do not observe large differences in the likelihood of different opinion distribution types.

In sum, the evidence produced by the entropy analysis (Figure 3D) in support of the proliferation-diversification hypothesis (H2) is weak. Although the average entropy of the final opinion distributions may exceed that of the baseline model when five mass media systems are included, the trend is not a linear increase, and the effects are not statistically significant. The opinion distribution analysis (Figure 4E) also does not provide clear evidence to support the hypothesis. On the one hand, having more than one mass media system leads to polarization. On the other hand, polarization is never the dominant pattern. Instead, we observe a trade-off between mainstreaming dominating with one or two mass media systems and homogenization dominating with more than two. In this transition, marginal groups assimilate into the mainstream, resulting in a single (albeit possibly more diverse) opinion group. If one considers the number of opinion groups as the sole metric for opinion diversity, increasing the number of media systems in fact leads to lower diversity.

Discussion

Decades of empirical research have uncovered diverse impacts of mass media, leading to debates about the effects of high-choice media environments on opinion polarization. Our agent-based model is designed to test the mainstreaming hypothesis of cultivation theory in the age of social media. It also examines the potential of mass media to alleviate political polarization. To this end, our model integrates theories with seemingly competing assumptions and different mechanisms, including individual information processing and social network dynamics. This allows us to evaluate the role of mass media within a complex information ecosystem without an ideological or theoretical angle predetermining the results. Unlike regression-based approaches, ABM also allows us to capture dynamic and non-linear effects. Finally, simulation models offer diagnostic insights by allowing comparison with empirical observations.

Somewhat unexpectedly, the current study shows that the mainstreaming effects of mass media can persist even when the number of media increases and the audience becomes fragmented. This challenges the notion that a high-choice media environment leads to or exacerbates polarization in the age of social media. This result becomes less surprising when considering our model's use of an algorithmic mean as the media message value function, which employs an egalitarian logic by assigning equal weight to all audience opinions. Although each mass media system is only responsible to its audience, multiple mass media systems would collectively function as a mainstreaming force. A potential direction for future work is to explore how these results would change if opinions were already polarized prior to the introduction of mass media.

We observe that opinions converge quickly (in the first 2,000 simulated time steps) and change little during the remainder of the simulation. This captures the formation-maintenance dynamics of opinion formation when a new issue surfaces: initially characterized by a diversity of views, individuals quickly cluster into distinct opinion camps, after which these established opinions become resistant to change (Briñol & Petty, 2015).

The model does not replicate the increasingly polarized opinions observed in contemporary U.S. national politics. This discrepancy suggests that growing numbers of media channels alone may not be the primary driver of escalating polarization. This finding underscores the importance of examining the content-creation logic utilized by different media outlets, rather than focusing solely on the proliferation of information sources. Future simulations could incorporate diversified media message functions or adjust media message functions in response to shifting opinion landscapes. This insight also motivates further empirical studies to explore changes in content-creation logic. Future research should extend beyond content analysis to include investigations of the gatekeeping processes and sociological forces that influence media content creation, an area often neglected in media effects research (Shoemaker & Reese, 2013).

While the media message functions used in our design might not fully reflect the reality of the U.S. media environment, they may be more representative of countries with different media systems, such as those with strong state-controlled media (Chadwick, 2017). From a social engineering perspective, adopting ideologically homogeneous mass media systems can be effective at mitigating social divisions but is not without drawbacks. Empirical evidence suggests that a homogeneous media system may restrict healthy opinion plurality and contribute to the rise of authoritarianism and anti-democratic sentiments (Shanahan & Morgan, 1999). Our findings illustrate that mainstreaming can lead to marginalization: in scenarios dominated by a single mass media system, our model predicts the emergence of one mainstream group and the marginalization of others. This marginalization underscores the critical role of “avoidance” in opinion formation (Chaiken, 1987). Audiences with views divergent from mainstream narratives may resist assimilation, leading to psychological resistance and potential boomerang effects (Hart & Nisbet, 2012). Such insights challenge the notion that the proliferation of ideologically radical media is necessary for extreme values to form.

While ABM offers a valuable framework for scholars to explore or revisit media effects theories from a complex systems perspective, this approach is not without limitations. Most social science models, including ours, function as experiments on theoretical ideas and assumptions that are often simplified and open to debate. Although our model is informed by theoretical and empirical research, validating agent-based models with empirical evidence remains a challenging task. The integration of large language models (LLMs) into ABM could enhance realism and empirical grounding in model design (Gurcan, 2024; Park et al., 2023). The use of LLM-driven agents to study opinion formation exemplifies this potential (Chuang et al., 2023), although this approach also presents risks (Bail, 2024). Future research could extend our approach by developing specialized LLM-powered media agents to simulate and analyze media effects.

Our model, inspired by the idea of mainstreaming in cultivation theory, serves as a robust framework for understanding the effects of a high-choice media environment. Our study reveals that the mainstreaming effects of mass media can persist when the number of media sources increases, challenging assumptions about media-driven polarization. The model underscores the potential of mass media systems with egalitarian content creation logic to mitigate political polarization, even in highly fragmented audience landscapes. Looking forward, it is essential to develop prescriptive models that foster societal collaboration while preserving a robust diversity of opinions. The ultimate aim of such a balance is to enhance constructive dialogue and informed decision-making in society.

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Table 1
Parameter default setup

Parameter	Description	Default value/range
Networks		
N	Number of agents	100
E	Number of links	400
Agents		
ϵ	Tolerance level	.5
μ	Strength of social influence	.3
p	Probability to post own value or repost a compatible message	.5
q	Probability to unfollow an incompatible friend *and* follow a new compatible friend	.3
l_i	Screen size, i.e., the maximum number of recent messages that one active user can process	$[2, 3, \dots, 10]$
ρ_0	Random noise for opinion update	$[-.2, .2]$
Mass media		
s	Probability to post media messages	.5
ρ_1	Random noise for media message value variation	$[-.25, .25]$

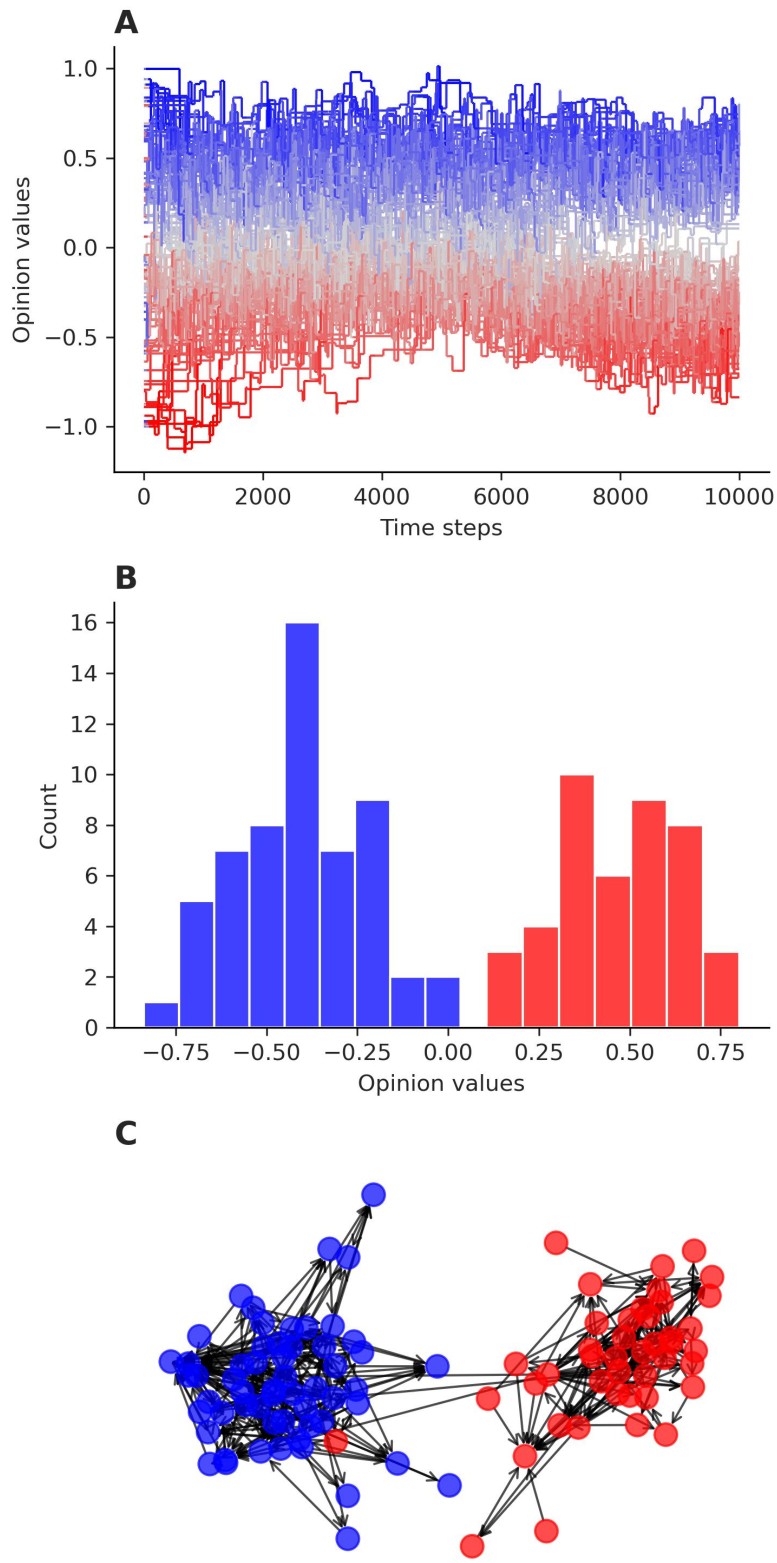

Figure 1

Opinion and network evolution of the baseline model. ***A*** *Opinion evolution of the baseline model (no mass media). Colors represent the range from* -1 *(red) to* $+1$ *(blue)* ***B*** *The final opinion distribution. The baseline model typically produces polarized opinions.* ***C*** *The final network structure. Edges are directed from follower to followed user. The baseline model typically renders two communities corresponding to the final opinion distribution.*

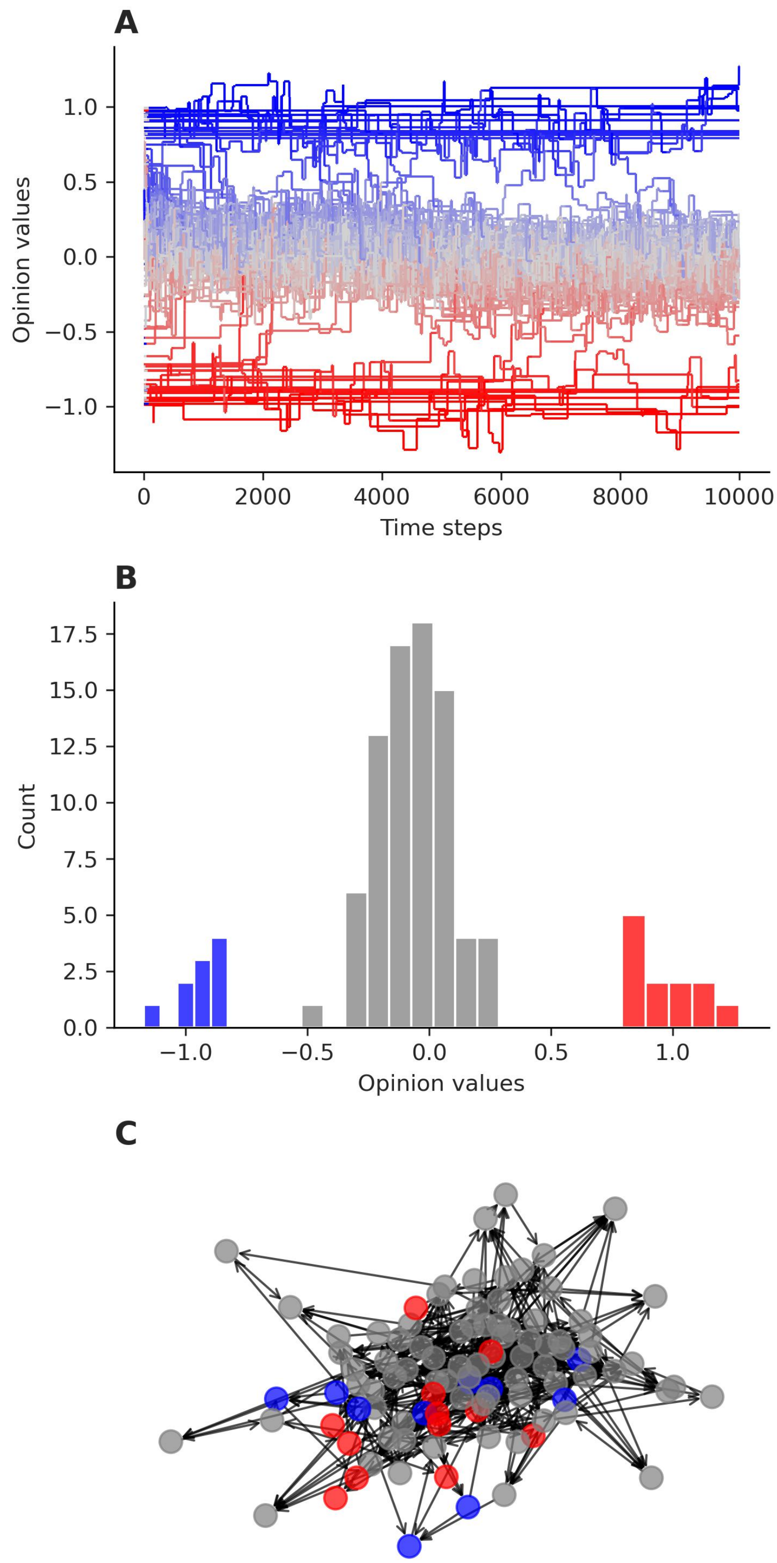

Figure 2

Opinion and network evolution in one simulation with a single mass media system having a 90% audience reach. A *Opinion evolution.* ***B*** *The final opinion distribution. This model typically produces a multimodal distribution characterized by a mainstream opinion group in the middle and two marginal groups occupying the extremes.* ***C*** *The final network structure. We do not observe a strong modular structure corresponding to the final opinion distribution.*

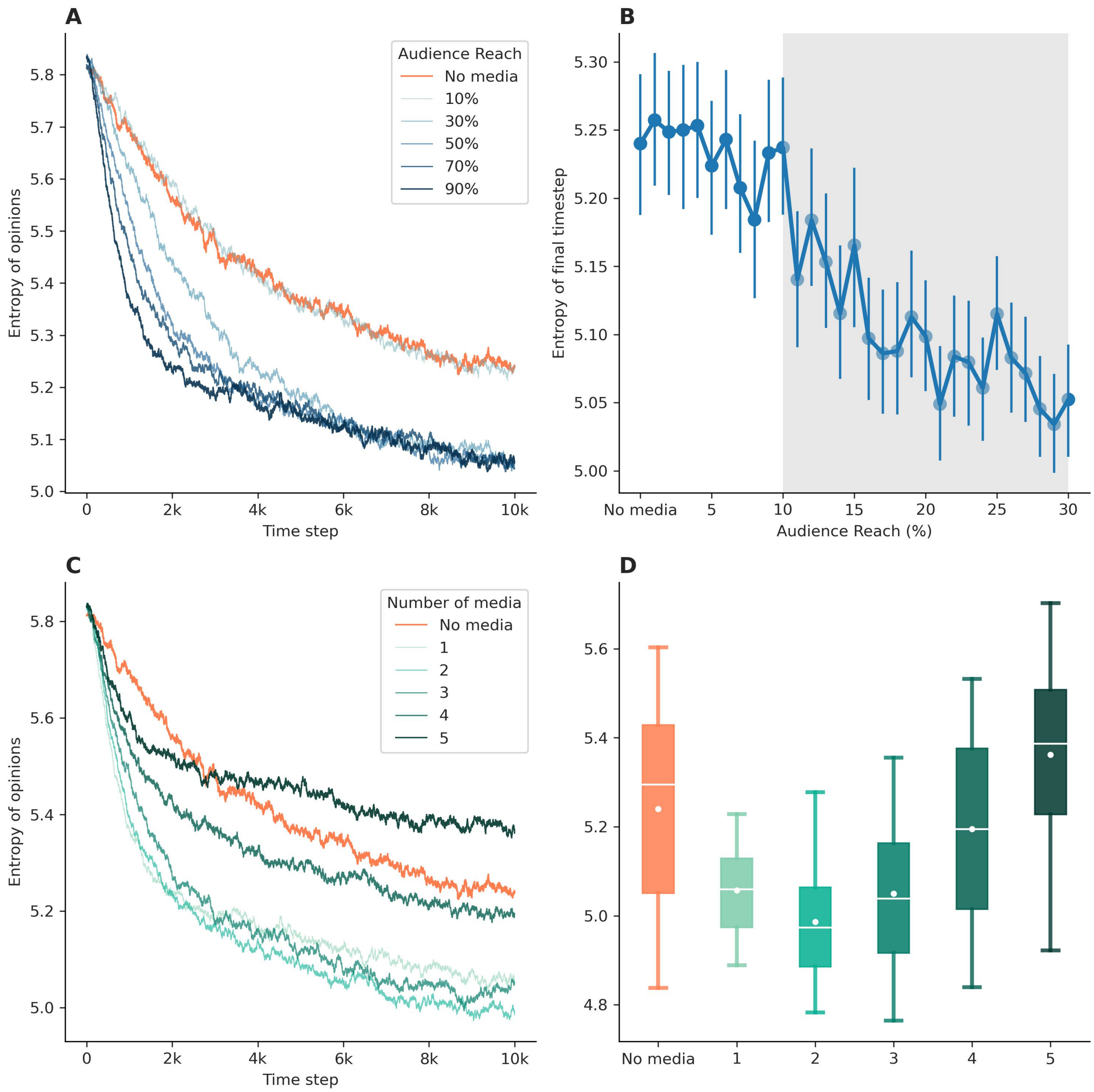

Figure 3

Opinion diversity analysis. A *Compared to the baseline, a single mass media system with a sufficient audience reach causes opinion heterogeneity (measured by entropy) to decrease more rapidly.* ***B*** *When the mass media system's audience is below 10%, no effect is observed; between 10–30% (gray area), higher mass media audience reach leads to lower entropy. Error bars correspond to ±2 standard errors, produced by 100 simulations.* ***C*** *Increasing the number of mass media systems affects opinion heterogeneity.* ***D*** *Media proliferation has a non-linear effect on the final opinion diversity.*

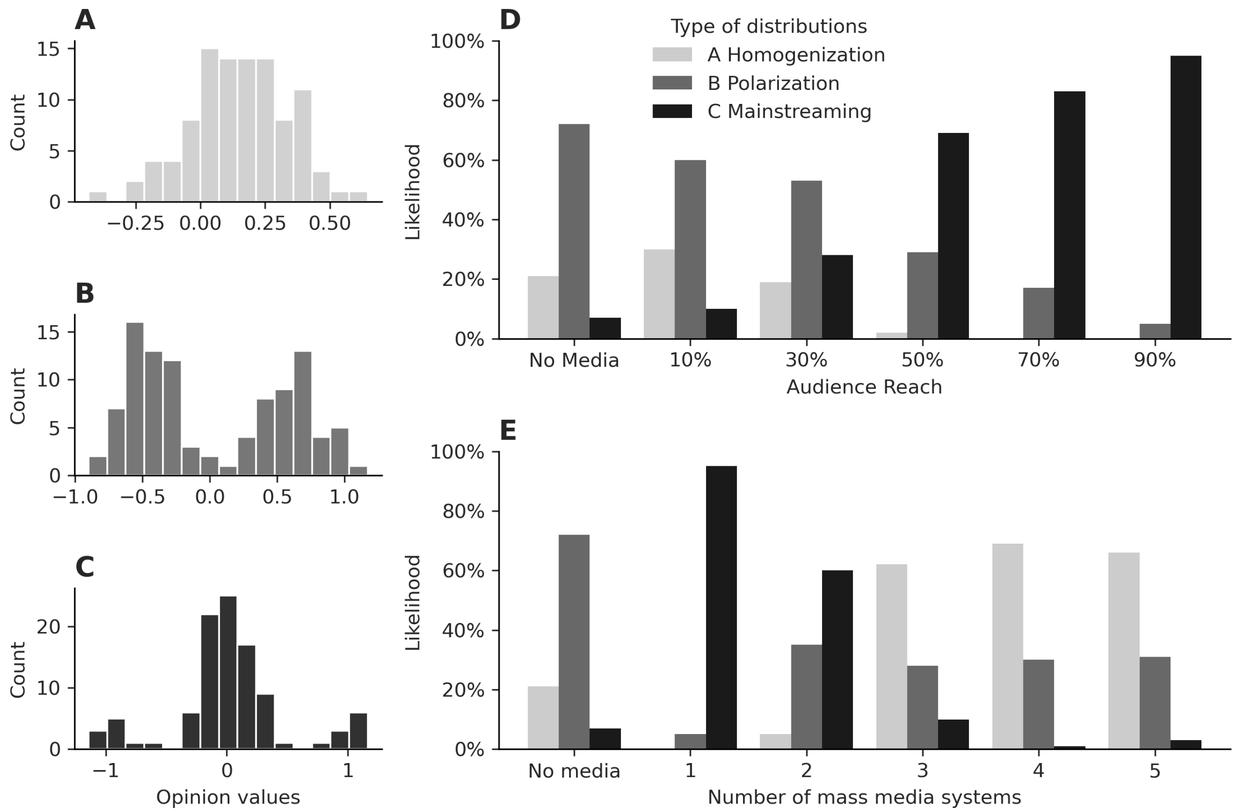

Figure 4

Opinion distribution analysis. *Panels **A–C** illustrate the three typical final opinion distributions with lines showing the kernel density. **A** Homogenization: A single opinion cluster with a normal distribution. **B** Polarization: A bimodal distribution. **C** Mainstreaming: A multimodal distribution with a mainstream opinion group in the middle and two marginal groups occupying the extremes. **D** Effects of increasing the audience reach of a single mass media on the likelihood of final opinion distributions. **E** Effects of the proliferation of mass media systems with an overall 90% reach on the likelihood of final opinion distributions.*