How social media creators shape mass politics *

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Political apathy and skepticism toward traditional authorities are increasingly common, but social media creators (SMCs) capture the public's attention. Despite their prominence, whether these seemingly-frivolous yet engaging actors shape political attitudes and behaviors remains largely unknown. Our field experiment estimates the impact of encouraging Americans aged 18-45 to follow five progressive policy-minded SMCs on Instagram, TikTok, or YouTube for five months. Participants are randomly assigned to follow SMCs producing predominantly-apolitical and non-partisan or predominantly-political content; we cross-randomize recommendation-only or additional financial incentives to follow assigned SMCs. We then measure participants' political engagement, policy attitudes and priorities, progressive worldviews, voting behavior, non-electoral participation, and institutional and interpersonal trust. The comparison between treatment conditions, and against a pure control and several placebo groups, will evaluate the persuasive potential of sustained exposure to previously-unfollowed SMCs. Our findings will illuminate the role of SMCs as modern-day opinion leaders defining political communication in American democracy.

[Important note: Data collection is now concluding, so this submission is a pre-registered report (approximately the final paper without results). However, the initial midline and initial endline findings are interesting, showing that both predominantly apolitical and predominantly political social media creators significantly shaped political attitudes, perspectives, and preferences during the 2024 US presidential campaign. The full paper will of course be complete by the time of the conference.]

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1 Introduction

The way Americans consume political information is undergoing a transformation. Just a decade ago, television and newspapers were the dominant sources of news, but social media is now the leading platform where Americans obtain news (Newman et al. 2023). This shift is particularly pronounced among young adults: 76% of those aged 18–29 report getting news at least occasionally from social media, which they identify as their most preferred outlet (Pew Research Center 2022). While platforms like Facebook and Twitter once dominated the social media landscape and prioritized content from traditional media outlets, Gen Z and Millennials increasingly turn to video-driven platforms to consume and engage with news (McClain 2024). This was particularly true of the 2024 U.S. election campaign, with the *New York Times* calling it the "the TikTok election"[1] and the *Washington Post* proclaiming paid-for content on Instagram, TikTok, and YouTube to be "the new dark money."[2]

A distinctive feature of political information on these video-driven social media platforms is that it rarely comes from conventional news sources or adopts the format of newscasts or talk shows. Much of it is instead produced or shared by social media creators (SMCs), who operate outside the control of traditional media gatekeepers (Pew Research Center 2024; Zhuravskaya, Petrova and Enikolopov 2020). The political ideas SMCs make accessible can be embedded within their usual entertainment or lifestyle content, blurring the boundaries between news and non-news; for predominantly-political SMCs, it is their core content. With 37% of adults aged 18-29 and 26% aged 30-49 now regularly getting news about politics from SMCs (Pew Research Center 2024), the ever-widening array of media choices enables citizens to opt out of traditional news outlets adhering to stronger journalistic standards of being "accurate, fair and thorough"[3] and into content of their choosing (Arceneaux and Johnson 2013; Kim 2025; Prior 2007).

While some research highlights social media's detrimental impacts for users (e.g. Allcott et al. 2020; Braghieri, Levy and Makarin 2022), SMCs could educate and engage citizens politically. On their face, SMCs' might seem frivolous or lacking in gravitas. However, by reaching large audiences, SMCs can introduce and provide information about particular issues, frame news and policy debates, and encourage political participation. SMCs thus have the potential to cultivate and steer political attitudes, concerns, and behaviors or serve as gateways to other political content. Moreover, SMCs may be particularly effective messengers because of their perceived authenticity, credibility, and trustworthiness, deepening their resonance with followers (Hund 2023; Lou and Yuan 2019; Schmuck et al. 2022; Xiao, Wang and Chan-Olmsted 2018). This combination of accessibility and trust positions SMCs as modern-day "opinion leaders" in Katz and Lazarsfeld's (1955) two-step flow

[1] *New York Times*, "The Election Has Taken Over TikTok," October 21, 2024, www.nytimes.com/interactive/2024/10/21/business/media/2024-election-tiktok-trump-harris.html.

[2] *Washington Post*, "The new dark money: How influencers get paid big bucks to court your vote," October 26, 2024, www.washingtonpost.com/technology/2024/10/26/social-media-influencers-election-money-campaigns/.

[3] Society of Professional Journalists, Code of Ethics. https://www.spj.org/ethicscode.asp.

of communication, shaping both what political information younger adults encounter and how they interpret it.

The growing integration of SMCs into electoral campaigns and government and non-profit organizations' education campaigns, especially during the 2024 election, underscores the urgency of understanding their potential to shape public opinion. The 2024 Democratic National Convention included SMCs in its official program for the first time while Kamala Harris went on the popular *Call Her Daddy* podcast. Donald Trump credited creators like Joe Rogan and the Nelk Boys—better known for entertainment than politics—as pivotal to his 2024 campaign's success. Moreover, state and local governments have enlisted micro-influencers to promote vaccines or counter misinformation, as seen in Colorado, Oklahoma, and Minneapolis. Non-profit organizations, such as the ACLU, Planned Parenthood, Turning Point USA (TPUSA), and World Wildlife Fund, now also create sponsored content with SMCs to educate the public on their issues or to advance their policy positions and worldviews. Despite these widespread adoptions, the power of SMCs is often assumed rather than proven, leaving whether and how SMCs impact politics as a critical gap in our understanding of the evolving landscape of American political discourse.

SMCs' persuasive potential may depend on their content and reach. At one end are lifestyle-focused SMCs, whose primary content revolves around topics like food, fashion, wellness, humor, or popular culture. On the rare occasions these creators weave policy or politics into their posts, they offer a subtle way to engage a broader and less politically engaged audience, potentially with limited resistance or backfire effects. At the other end of the spectrum are explicitly political SMCs, who center their content on breaking news, policy debates, or partisan politics. These creators tend to attract politically-engaged and often ideologically-aligned audiences, potentially limiting their appeal and credibility among politically indifferent users. Whether SMCs producing high or low volumes of political content are more influential is thus theoretically uncertain: while predominantly apolitical and non-partisan SMCs may generate greater engagement and credibility among more politically-disengaged audiences, predominantly political SMCs produce more politically-topical content.

This paper investigates whether and how sustained exposure to content produced by different kinds of SMC affects the political beliefs, attitudes, and behaviors of Millennial and Gen Z adults. Conducting the first field experiment of its kind, we examine the effects of encouraging five months of exposure to content from previously-unfollowed SMCs during the 2024 U.S. presidential election campaign. To do so, we recruited a panel of 4,716 Americans aged 18-45 who already use Instagram, TikTok, or YouTube at least three days a week. All participants completed our baseline survey in early August 2024, while our outcomes are measured in midline and endline surveys in October/November 2024 and January 2025 as well as using administrative data wherever possible. Our primary preregistered outcomes will capture indexes of political engagement, progressive policy attitudes, progressive policy priorities, political worldviews, favorability toward and voting for

the Democrat over the Republican party, electoral participation, progressive non-electoral participation, and institutional and interpersonal trust.

Our treatment conditions encouraged participants to start following either five *predominantly-apolitical* SMCs occasionally producing educational content on politics or policy issues or five *predominantly-political* SMCs producing progressively-slanted content on Instagram, TikTok, or YouTube between mid-August and late December 2024. The apolitical SMCs integrate non-partisan policy information alongside their usual largely apolitical content to educate their audiences about traditionally progressive issues relating to democracy, economic justice, climate change, and public health. In contrast, political SMCs specialize in covering news and commenting on current affairs from a progressive, and often partisan, perspective. For each treatment group, we devised a machine learning algorithm to recommend the five SMCs best matching participants' interests within curated pools of 20 apolitical or political progressive SMCs producing no more than 20 minutes of content in a typical week.[4] We compare these treatment arms with participants assigned to similarly consume entirely non-political SMCs, receive SMS and email messages summarizing similar non-partisan policy information, and a pure control condition. To address the risk of non-compliance, we further cross-randomized whether participants assigned to the apolitical, political, or placebo SMC conditions were encouraged to consume assigned SMCs' content with just our recommendation, a small financial incentive for following recommended SMCs, or nine biweekly quizzes each rewarding participants with $20 for correctly answering at least four of five questions about recent SMC content.

Our findings promise to illuminate if and how beginning to follow different types of SMCs—and the content they may subsequently lead individuals to consume—influences mass beliefs about policy, attitudes, and behaviors and to provide actionable insights for policymakers and organizations leveraging SMCs to advance their goals. As the ways people engage with politics and policy evolve, we expect to advance understanding in several principal domains by establishing the extent to which SMCs' political content engages and ultimately informs or persuades their followers.

First, our study contributes to the emerging literature on SMCs by conducting the first large-scale field experiment to assess their political influence through sustained interaction with previously-unfollowed SMCs. Short-term survey experiments (Audrezet, De Kerviler and Moulard 2020; Hoffner and Bond 2022; Lou 2022; Rojek 2015) struggle to capture the parasocial relationships that may underpin SMCs' impact, the volume of SMC content, or its enduring effects. In contrast, our study encourages participants—whether through recommendations or financial incentives—to establish deeper connections with assigned SMCs and engage meaningfully with substantial amounts of content in a more naturalistic environment. The experiment takes place during the high-stakes context of a U.S. presidential campaign, likely underestimating SMCs' influence during less politically saturated periods. Distinct from the mixed evidence of social media *platforms*' political impact

[4]We also recommended several SMCs producing larger amounts of similar content, but focused our encouragements on SMCs requiring less time commitment.

(e.g. Allcott et al. 2020, 2024; Asimovic, Nagler and Tucker 2023; Ventura et al. 2023),[5] we shift the conversation from the overall effects of Facebook and Twitter to the role of SMCs on today's most popular social media platforms for news. By examining if and how SMCs engage, inform, or persuade younger voters—an increasingly critical but challenging demographic to reach—our findings will illuminate not only whether SMCs matter, but also how they can serve as a powerful and policy-relevant tool for modern political and policy engagement.

Second, we expand the study of exposure to slanted and partisan media to SMCs engaged with traditionally progressive policy issues. Prior studies largely find that TV channels with different stances, like Fox News, exert substantial influence over individuals who choose to consume them (Broockman and Kalla forthcoming; DellaVigna and Kaplan 2007; Hopkins and Ladd 2014; Martin and Yurukoglu 2017); newspapers, whether offline (Gerber, Karlan and Bergan 2009) or online (King, Schneer and White 2017; Levy 2021), can also affect beliefs and set the agenda. But traditional media outlets possess considerable expertise and rely on large reporting and production budgets. This study will reveal whether SMCs who break this mold, but whose lack of formal credentials could be offset by the strong personal connections they build with audiences, can similarly shape public beliefs or opinion. We further advance the media effects literature by comparing SMCs who differ in whether their content is predominantly political or apolitical, and will thus test whether "soft news" more effectively engages or resonates with politically-disinterested consumers (Baum 2002; Baum and Jamison 2006) in this social media era. Moreover, our varying intensity of encouragements to follow SMCs will provide a rare opportunity to observe selection into content consumption. In today's high-choice media environment, where audiences actively choose what to engage with (Arceneaux and Johnson 2013; Kim 2025; Prior 2007; Settle 2018), understanding these selection dynamics is critical for assessing the scope for slanted media and messaging to shape mass political attitudes or behaviors.

Finally, by focusing on participants aged 18-45, we provide critical insights into how to engage younger generations disillusioned with and disconnected from traditional news sources. SMCs offer a promising solution by embedding political messages within entertainment-driven content, making politics more accessible and relatable. To the extent that SMCs serve as opinion leaders, our study builds on the two-step flow of communication framework (Katz and Lazarsfeld 1955; Lazarsfeld, Berelson and Gaudet 1948) to assess whether trusted intermediaries can reconnect disengaged audiences with political information. Unlike traditional media, which often struggles to engage this demographic, SMCs operate on platforms that younger adults already frequent and foster trust through authentic, relatable communication. While SMCs cannot replicate the depth or institutional credibility of traditional journalism, they complement it by providing an accessible gateway to political awareness and participation in ways legacy outlets cannot. Our findings will

[5]Such large-scale deactivation experiments quantify the effect of (not) using a platform (e.g. being on Facebook), rather than dissecting the impact of specific types of content on social media. Although a deactivation design could be extended to focus on particular SMCs, a deeper challenge is that such a study may not test a meaningful comparison if those who deactivate have already internalized the effects of treatment.

reveal both the opportunities and challenges of using SMCs to revitalize political engagement for the next generation.

2 Social media creators as opinion leaders

Interpersonal communication has long been central to how individuals make sense of politics (Harari 2015; Katz 1957; Katz and Lazarsfeld 1955; Lazarsfeld, Berelson and Gaudet 1948). Katz and Lazarsfeld's seminal two-step flow of communication emphasized the role of opinion leaders—trusted figures within social networks—in reporting and interpreting political-relevant information for others. Historically, these opinion leaders were local figures such as church leaders, union organizers, or community activists who wielded influence within close-knit social networks (Katz 1957; Katz and Lazarsfeld 1955). They acted as intermediaries, filtering information from mass media and helping others navigate issues of public concern. However, the rise of digital technologies and fragmented media consumption patterns is reshaping how opinion leadership operates.

Social media platforms have enabled a new generation of opinion leaders—social media creators (SMCs)—to build substantial audiences far beyond the constraints of geographic or social proximity. Many SMCs gain followings for non-political content, but some also blend lifestyle content with education or advocacy to address political and social issues (Casaló, Flavián and Ibáñez-Sánchez 2017; Djafarova and Bowes 2021). Others appeal to narrower audiences by specializing in current affairs and politics. For younger generations, SMCs have become key sources of news and perspectives, filling the void left by declining local journalism and waning trust in traditional media (Hoffner and Bond 2022; Lou 2022); nearly two in five people aged 18 to 29 turn to SMCs as a regular news source (Pew Research Center 2024).

Whether these dynamics translate into meaningful political influence, however, remains an open question. While SMCs have demonstrated the ability to engage their audiences and advertise products, the extent to which they can shape policy and political attitudes or behaviors is less clear. As political elites increasingly partner with SMCs to amplify their messages, understanding if and how SMCs impact political engagement is essential.

2.1 How SMCs might matter politically

SMCs are distinct from traditional journalists in their expertise, autonomy, and style. First, unlike reporters who rely on rigorous training and institutional resources for background research and fact-checking, SMCs often lack formal credentials in journalism or political commentary. Second, SMCs also operate with a high degree of autonomy, producing content independently without the oversight of institutional editors, professional guidelines, or owner influence that constrains traditional journalists. This freedom allows SMCs to express personal opinions and embed subjective perspectives. Finally, SMCs generally differ in their style and delivery, blending entertainment with

commentary through informal tones, humor, personal anecdotes, and direct audience engagement, rather than following more formal newscast and political discussion formats.

These differences could lead skeptics to question SMCs' potential to exert political influence. The absence of traditional expertise or institutional credibility among many SMCs could undermine their ability to effectively address complex or nuanced issues Alt, Marshall and Lassen e.g. 2016; Lupia and McCubbins e.g. 1998, while SMCs may primarily appeal to like-minded followers who already share their political views (e.g. Stroud 2008). Nonetheless, we argue that SMCs are still influential, especially among younger audiences disengaged from traditional political information sources, by both providing a gateway into political discourse and leveraging their distinctive features to enhance their capacity to persuade.

2.1.1 Capacity to reach and engage audiences

For any tangible media effects to surface, the audience must be engaged by content (Zaller 1992); as Prior (2009, 130) puts it, "the causal chain starts with exposure." Yet, in today's high-choice media environment, exposure to political information is increasingly uncertain. Indeed, many consumers avoid political content when they can (Arceneaux and Johnson 2013; Prior 2007). Traditional news audiences have declined across nearly every metric (Bakshy, Messing and Adamic 2015; Hayes and Lawless 2021; Toff, Palmer and Nielsen 2023; Krupnikov and Ryan 2022; Wojcieszak et al. 2022), highlighting the growing importance of achieving exposure as a foundational step for any political communication effects (Kim 2025). Amid these challenges, SMCs are particularly well-positioned to effectively reach and engage audiences.

SMCs generally attract audiences primarily seeking entertainment, with social media platforms enabling incidental exposure to political content as a by-product of consuming lifestyle or entertainment content (Baum 2011; Bergström and Jervelycke Belfrage 2018; Downs 1957; Prior 2007). Social media's ability to embed political messages within or alongside non-political streams lowers barriers to political engagement, serving as an accessible entry point for less politically-engaged audiences (Newman et al. 2021; Settle 2018). This aligns with insights from infotainment research, which shows that entertainment-oriented content—such as "soft news" or late-night talk shows—can occasionally expand the size of the attentive public by covering significant events or embedding political messages (Baum and Jamison 2006; Baum 2011; Moy, Xenos and Hess 2005; Reinemann et al. 2012). Notably, the capacity of SMCs to reach a broad audience is amplified by the recommendation algorithms of popular social media platforms. These algorithms prioritize engagement, frequently pushing highly shareable or emotionally resonant content to wider audiences, regardless of followers (Bucher 2018; Cotter 2019; Suarez 2022).

Another factor that helps SMCs engage audiences is the parasocial relationships they develop (Giles 2002). Unlike traditional media figures, SMCs often cultivate a sense of intimacy and relatability through informal and seemingly-unfiltered content (Casaló, Flavián and Ibáñez-Sánchez

2017; Rasmussen 2018). The type and format of content they produce—ranging from live streaming, content tailored to followers' comments, and Q&A sessions—create a real-time interactive dynamic, strengthening the illusion of a two-way relationship between creators and their followers (Ferchaud et al. 2018; Yuan and Lou 2020). This perceived closeness can increase engagement with their messages, even when discussing political topics (Hasell and Chinn 2023; Riedl et al. 2021). By leveraging these relationships, SMCs can convey political messages in ways that traditional media outlets struggle to replicate.

2.1.2 Potential to persuade followers

The study of political persuasion, particularly the factors that facilitate it, has a rich history with varied empirical findings pointing to multiple pathways (see Druckman 2022). Sustained persuasion could update citizens' preferences, beliefs, or priorities, for instance by deciding which topics to emphasize (e.g. McCombs 2018), selectively providing information about a given topic (e.g. Broockman and Kalla forthcoming), or framing issues and offering argumentation (e.g. Chong and Druckman 2007; Leeper 2020). Despite the diversity in this literature, several generalizable factors suggest SMCs could act as effective agents of persuasion through each of these mechanisms: trust in the source, the emotional resonance of the message, and the receptiveness of the audience.

SMCs leverage the trust and credibility they cultivate through parasocial relationships with their audiences. These relationships, characterized by a sense of intimacy, relatability, and authenticity, make audiences more receptive to the messages conveyed by SMCs (Hoffner and Bond 2022; Lou 2022). Unlike purely informational media, SMCs deliver content in a personal and approachable manner, reducing psychological resistance to controversial or unfamiliar ideas. This relational dynamic fosters a sense of trust, particularly among younger audiences who are skeptical of traditional media but view SMCs as credible and relatable sources of information.

This trust plays a crucial role in persuasion, especially when individuals process messages under "low-effort" cognitive modes (Chen and Chaiken 1999; Petty and Cacioppo 1986). When people lack the motivation or capacity to thoroughly analyze the content of a message, they often rely on peripheral cues, such as the perceived trustworthiness of the speaker, to guide their opinions (Carlson and Settle 2022; Druckman 2022; Sinclair 2012). SMCs, with their seeming authenticity, can serve as trusted sources, particularly for followers who are less politically engaged or knowledgeable. When SMCs advocate for a political stance, their followers may accept these views based on the trust they have in the creator rather than scrutinizing the argument itself. This reliance on peripheral cues makes SMCs particularly influential in shaping attitudes on complex political issues, where detailed evaluation is less likely.

SMCs are also particularly effective at persuasion due to the emotional resonance of their messages and the receptiveness of their audiences. Emotions play a pivotal role in persuasion by capturing attention and motivating action (Albertson, Dun and Gadarian 2020), and SMCs excel at em-

bedding political messaging within emotionally charged, entertaining content. By weaving political ideas into humorous skits, personal anecdotes, or engaging narratives, SMCs make their messages feel approachable and non-confrontational, bypassing psychological resistance that often arises with overtly political content (Young 2020; Mutz and Nir 2010; Settle 2018). For example, an SMC addressing climate change through a relatable story or comedic video can provoke thought and inspire action more effectively than a formal news report, as audiences are drawn in by the emotional appeal and subtlety of the presentation.

2.1.3 The balance between political and non-political content

SMCs vary significantly in the extent to which their content focuses on politics and policy, ranging from creators who primarily produce apolitical content to those whose output is dominated by political commentary. This variation highlights another key dimension of their persuasive potential: the balance between political and non-political content. While predominantly-political SMCs may influence their audiences through the frequency or depth of their political messaging, predominantly-apolitical SMCs could reach broader audiences by embedding occasional political commentary within entertainment-driven narratives. The relative persuasive potential of these approaches remains theoretically ambiguous.

On one hand, predominantly-political SMCs expose their followers to more political content than predominantly-apolitical SMCs. Whether by consolidating views on a given issue or holistically shaping views on lots of different issues, a large quantity of political content has obvious potential to influence policy positions, issue salience, and ultimately preferences between political candidates or parties. As such, online political commentators like Philip DeFranco, Candace Owens, or Hasan Piker could substantially influence their followers.

On the other hand, a focus on politics may jeopardize an SMCs' influence. Since politics is not a primary topic of interest for most social media users, they may be less likely to consume the content of predominantly-political SMCs (Prior 2007). Those who opt to expose themselves to this content may already be well informed and possess strong political views, due to their greater interest in politics, or already share the views of the SMC (Stroud 2008). Additionally, frequent and overtly partisan political content can weaken the parasocial bond with followers, alienating those who disagree with an SMC's stance or perceive them as less independent.

In contrast, by only occasionally addressing the topics of politics and policy, predominantly-apolitical SMCs may generate greater exposure and have a stronger persuasive impact. Their infrequent but well-placed political content—embedded within broader entertainment narratives—may engage more diverse audiences and persuade more effectively. Figures like Alex Cooper or Joe Rogan, who periodically weighed in during the 2024 election campaign, exemplify how sporadic engagement can broaden reach and influence. Whether this approach offsets the advantage of sustained political messaging is an important open question.

2.2 Implications of following progressively-minded SMCs

The preceding discussion highlights how SMCs could shape the political beliefs, attitudes, and behaviors of their followers. We apply these insights to SMCs producing progressive-slanted political content—the focus of our field experiment during the 2024 U.S. presidential election campaign—to generate the central hypotheses driving this study. We view progressivity as a liberal-leaning political ideology that advocates a central role for government and active citizen engagement in democratically addressing social, economic, and political inequalities through transformative policy and systemic reform. This term does not necessarily refer to electoral messaging. Today, key planks of the progressive policy agenda include mitigating income inequalities, increase social justice, universal healthcare coverage, and combating climate change. Achieving these goals relies on reducing corporate power through greater market regulation, increasing labor rights, and active and broad-based involvement in and support for democracy. Our study evaluates how exposure to SMCs emphasizes these issues and narratives affects participants' engagement with progressive ideas, policy attitudes, political participation, and support for political parties and candidates.

Our first hypothesis is that exposure to SMCs' progressive policy content will lead participants to adopt more progressive policy positions, concerns, and worldviews, while also increasing their political participation. The direction of persuasion is expected to align with the progressive slant of the content, given that the average American lies to the right of the progressive positions under study. In the current U.S. political context, these shifts may also be reflected in greater support for the Democratic Party—including increased favorability, more positive appraisals of its candidates and performance in office, and vote choice—relative to the Republican Party as well as increased advocacy for progressive causes.

While these predictions likely apply to progressive messaging through any medium, we further hypothesize that SMCs are particularly impactful messengers. Their authenticity, relatability, and ability to embed political messages within entertainment-driven narratives make them more effective at engaging and persuading audiences than the same content delivered without SMCs. For the reasons described above, it is unclear whether content produced by predominantly apolitical or predominantly political SMCs is more influential: political SMCs may increase exposure to progressive ideas due to their greater production of such content, but their overtly political nature could reduce engagement or credibility. We proceed to experimentally test these hypotheses and thus evaluate the strengths and limitations of SMCs as vehicles for communication.

3 Experimental design

During the 2024 U.S. election campaign and its immediate aftermath, we investigate the consequences of adults aged 18-45 being encouraged to follow SMCs over a sustained period. Drawing information from the Better Internet Initiative (BII), a program focused on supporting non-partisan

educational policy content through SMCs, our field experiment evaluates the extent to which five months of exposure to SMCs—who produce either predominantly apolitical content or predominantly political content—shapes public opinion and political behaviors. We next describe our survey panel, treatment conditions (and encouragement to engage with treatment), study design, primary outcome measures, and estimation strategy.

3.1 Sample of panelists

In August 2024, we recruited 4,716 American social media users aged 18-45 for this three-wave panel study. This sample is drawn primarily from Bovitz's Forthright pool of ∼300,000 U.S.-based panelists, but is supplemented by panelists from Esearch (2.6% of the sample) and SurveySavvy (19.8% of the sample).[6] These panelists were appealing because they usually take non-political consumer surveys and their comparatively high pay for completing online surveys generates low attrition rates. Participants are paid in redeemable credits within their platforms for completing 20-minute baseline, midline, and endline surveys in Qualtrics respectively commencing mid-August 2024, late October 2024, and early January 2025; see Appendix A.1 for detailed information on payment and research ethics.

Quota sampling was used to ensure balance over gender and a final sample that is broadly representative in terms of age, education, or partisan identification. To increase the likelihood that treated participants consume novel SMC content, we screened out the 14.3% of individuals who use neither Instagram, TikTok, nor YouTube more than two days a week, the 1.2% of participants who did not provide the name of their social media handle, and the 12.0% of participants who failed at least one of two attention checks. Table 1 reports summary statistics for our sample of younger adults, showing that our mean participant is 32.6 years old, has a household income of almost $70,000, only follows politics somewhere between "somewhat closely" and "rather closely" during a presidential campaign, and is more likely to be a Democrat than a Republican.

Our sample is used to consuming SMC content, but willing to consume new SMCs. The median participant spends 13 hours on Instagram, TikTok, and YouTube per week, mostly on their cell phone. They follow or subscribe to 1-10 social media accounts, which they are most likely to find on a social media platform and on average feel "moderately connected" to, and watch 11-15 videos per week from these accounts. The mean and median participant reports being "very open" to following new social media accounts; while they are neutral toward SMCs talking about politics, SMC content about news, public policy, or politics is less interesting to the average participant than lifestyle, entertainment, humorous, or science/tech/gaming content.

[6] We had targeted 4,550 baseline survey completes, but retain participants who were assigned treatment at the end of the survey but did not fully complete the survey. We excluded 28 ineligible participants, who were disqualified for one of four reasons: out of study age range; consumed social media irregularly and were not screened out due to a technical error; SMC recommendations (which are generated for all participants regardless of treatment status) did not pipe within Qualtrics; multiple responses from the same participant.

Table 1: Survey panel summary statistics

	Mean	Standard deviation	Minimum	Median	Maximum
Days using Instagram in average week	4.39	2.80	0	5	7
Days using TikTok in average week	3.46	3.00	0	3	7
Days using YouTube in average week	5.67	2.02	0	7	7
Hours using Instagram per week	6.05	9.71	0	3	140
Hours using TikTok per week	6.05	10.60	0	2	168
Hours using YouTube per week	12.62	15.42	0	8	168
Regularly use social media on phone	0.95	0.23	0	1	1
Regularly use social media on tablet	0.22	0.42	0	0	1
Regularly use social media on laptop/desktop computer	0.47	0.50	0	0	1
Social media accounts whose content you watch most of (mean value within 5 categories, topcoded at 50)	15.41	14.92	0	6	50
Weekly videos watched from followed social media accounts (mean value within 5 categories, topcoded at 15)	10.97	4.60	0	13	15
Encounter SMCs on social media platforms	0.79	0.40	0	1	1
Encounter SMCs through friends or family	0.39	0.49	0	0	1
Encounter SMCs by searching social media platforms	0.52	0.50	0	1	1
Encounter SMCs on other forums	0.35	0.48	0	0	1
Encounter SMCs in other ways	0.03	0.18	0	0	1
Connectedness to SMCs followed 5-point scale	2.76	1.09	1	3	5
Preference for SMCs to talk about politics 5-point	2.98	0.96	1	3	5
Openness to following new SMCs 5-point scale	3.86	1.08	1	4	5
Age	32.64	6.40	18	33	45
Male	0.44	0.50	0	0	1
Female	0.54	0.50	0	1	1
Non-binary	0.02	0.14	0	0	1
White	0.71	0.46	0	1	1
Black	0.23	0.42	0	0	1
Hispanic	0.16	0.37	0	0	1
Asian	0.07	0.25	0	0	1
American Indian, Alaskan Native, or Pacific Islander	0.04	0.20	0	0	1
At least a high school diploma (or equivalent)	0.97	0.16	0	1	1
At least some college credit	0.75	0.43	0	1	1
At least a complete bachelor's degree	0.38	0.49	0	0	1
Completed master's, professional, or doctoral degree	0.13	0.33	0	0	1
Heterosexual	0.76	0.43	0	1	1
Homosexual	0.05	0.21	0	0	1
Bisexual	0.12	0.33	0	0	1
Annual household income (mean value within 11 categories, topcoded at $250,000)	70,894.69	54,222.53	12,500	62,500	250,000
Follow politics closely 4-point scale	2.58	1.02	1	2	4
Think of self as Democrat or strong Democrat	0.32	0.47	0	0	1
Think of self as independent (including closer to Democrat or Republican)	0.41	0.49	0	0	1
Think of self as Republican or strong Republican	0.17	0.38	0	0	1
Liberal-conservative 7-point scale	3.59	1.59	1	4	7
Approve of way President Biden is handling his job	0.31	0.46	0	0	1
Intend to vote for Harris	0.49	0.50	0	0	1
Intend to vote for Trump	0.34	0.47	0	0	1

3.2 Treatment conditions

Our two primary treatment conditions encourage social media users to follow five progressively-minded SMCs they did not already follow from mid-August until late December 2024.[7] To assess the influence of different types of SMCs, these treatments are distinguished by whether participants are encouraged to follow SMCs whose core content is either predominantly apolitical or predominantly political. By predominantly political, we mean content that is focused on news, current affairs, and political institutions or actors and that has a particular perspective. By predominantly apolitical, we mean that an SMC's platform is only rarely used for any discussion of public policy or political issues, except as part of the non-partisan BII program. We compare these treatment conditions to a placebo group encouraged to consume content by entirely non-political SMCs.

Our apolitical progressive, political progressive, and placebo SMC conditions all comprise a mutually exclusive pool of 20 shorter-form SMCs, with at least ten SMCs regularly posting content on each of Instagram, TikTok and YouTube, and five further SMCs producing longer-form content. We recommended each participant five shorter-form SMCs—who typically produce less than 20 minutes of content a week—from the platform (or platforms) a participant regularly use and whose content we expected them to find engaging.[8] To identify engaging SMCs for each participant, we devised a matching algorithm using a neural network to recommend SMCs based on participants' stated interests and feedback on SMCs collected in a pilot study.[9] Participants in these treatment conditions were told that we had identified these recommendations based on their baseline survey responses, and were further provided with a several-sentence summary and an image of each account at the end of the baseline survey. We used the same approach to identify three of five SMCs producing more than 20 minutes of content a week, offering participants the opportunity to choose one to learn more about. Overall, the intensity of treatment is moderate in the context of the potentially large amount of time participants spend on social media.

Before describing each treatment condition in detail, we note two features of this intervention. First, by encouraging participants to follow *new* accounts for almost five months, we are attempting to build connections to SMCs through sustained exposure. We may thus underestimate the effect of SMC content on established followers, which is harder to estimate.[10] Nevertheless, social me-

[7] The topic and stance of SMCs inevitably varies because SMCs make their living by offering distinctive content. Nevertheless, we attempt to maintain some level of uniformity by first drawing from SMCs who were successful or unsuccessful applicants for the BII fellowship program; we then augmented this group for some treatment conditions by identifying similar accounts online.

[8] We define the platforms a participant regularly uses as the most platform they use on most days a week and any other platform they use no more than two fewer days per week. The baseline survey provided links to recommended SMCs via participants' most-used platform, but reminders provided links on all regularly-used platforms.

[9] We first characterized the regular content of all SMCs by coding characteristics such as gender, age group, ideology, and content aspects, including visual (e.g. fashionable, polished) and verbal (e.g. formal, assertive) styles, topics, and potential for polarization. Using baseline survey questions in our 278-person pilot, we aimed to minimize the distance between participants' preferences across multiple dimensions and these characterizations. Based on respondent feedback from the pilot endline survey, we trained a neural network recommendation model to predict the SMCs a participant in the full study would most enjoy consuming. Specifically, we used a hybrid collaborative and content-based filtering approach (He et al. 2017), where our model architecture included embedding layers for user and creator IDs to capture 200 latent factors, with embeddings concatenated and passed through multiple dense layers with Batch Normalization, LeakyReLU activation, and Dropout for regularization. The model was trained using early stopping to prevent overfitting, converging in 21 epochs to ensure stable performance on the validation set. For more details on the matching algorithm, see Appendix A.2.

[10] To capture this estimand, researchers might randomize content at the SMC level and measure outcomes among pre-existing followers. But this

dia users regularly start following new SMCs and understanding whether SMCs can engage and persuade new audiences is a key policy question. Second, our treatment conditions are internally heterogeneous by design, both to match participants with the SMCs we predict they would want to consume and because we cannot control either the platform algorithms or individual choices that shape social media content consumption beyond our encouragements to follow assigned SMCs. While our treatment conditions are more focused on a particular aspect of social media than studies leveraging differential access and deactivation to capture more general effects (e.g. Allcott et al. 2020; Braghieri, Levy and Makarin 2022), each treatment should still be considered as—and described by—the bundle of assigned content together with the content it leads participants to consume.

3.2.1 Apolitical progressive SMCs

Our 25 apolitical progressive SMCs are all drawn from the BII's annual fellowship program. This program helps more than 100 online content creators with mostly mid-sized followings—ranging from tens of thousands to millions—to produce Instagram, TikTok, and YouTube videos to educate their audiences about politics and policy issues associated with public health, democracy, economic justice, and climate change; the BII program does not have partisan electoral content. BII fellows are largely selected on the basis of their reach, audience rapport, and compatibility with the BII's values. Most fellows initially produce apolitical content, but join the BII fellowship to collaboratively produce around ten fact-checked and non-partisan social media videos over a year relating to the BII's four main policy themes.[11] Fellows are paid by the BII (at generally below-market rates) to produce these videos in their own voice and publish them on contracted social media platforms—one or more of Instagram, TikTok, or YouTube—either alongside or within their regular content.

Between August and October 2024, common topics of BII-supported videos included non-partisan voter registration and encouragements to vote and separate content concerning policy issues such as the adverse and inflationary effects of corporate power, the economic and practical consequences of climate change and government efforts to mitigate them, and the scope for government to reduce health care costs. November and December topics are expected to cover using public power to build an economy that works for everyone, reducing the costs of health care, encouraging COVID-19 and flu vaccinations, and resisting misinformation about climate change. By focusing on fellows due to produce most of their videos between August and December 2024, we expect study participants to receive an average of one BII-supported video per month from each assigned SMC.

faces two challenges: identifying a large group of SMCs willing to randomize the content that drives their business in a harmonized way and at an affordable price; and identifying and then reaching initial followers to conduct surveys, which is especially challenging on platforms that limit researchers' capacity to scrape follower lists (e.g. TikTok) or to do within surveys for rarely-followed SMCs. Deactivation studies that do not also vary SMC content would underestimate such effects because participants all received prior exposure.

[11] The BII draws from partner organizations that specialize in these four areas to source topical issues for SMCs to their content around. Quality control is maintained by the BII's internal project manager, who closely monitors and provides feedback on all BII-supported content to ensure its quality, accuracy, and informativeness. In line with the BII's non-partisan status, all BII-supported content posted by fellows is compliant with section 501(c)(3) of the Internal Revenue Code. Outside of BII-coordinated content, fellows are free to create content or pursue any other opportunity in their ordinary course provided that content does not promote inaccurate information.

For this treatment arm, we identified 20 fellows who were contracted to produce BII-supported content between August and December 2024 and who typically produce less than 20 minutes of content a week. Summary statistics of these SMCs' characteristics are shown in Table 2. Their content usually comes in the form of 1-2 minute videos and occasionally videos up to ten minutes long. In addition to the 20 SMCs producing relatively short and regular videos, we further included five fellows producing longer-form content, such as podcasts, live shows, and extended videos. The regular content of these predominantly apolitical SMCs includes celebrity and entertainment commentary, food, fashion, art production, lifestyle advice, interesting facts and history, and humorous sketches, while a couple focus singularly on science, beach trash collection, and disability rights. Despite being non-partisan, BII-supported videos highlighting salient policy issues thus represent a significant departure from these SMCs' normal content.

3.2.2 Political progressive SMCs

Our 25 political progressive SMCs comprise 7 BII fellows and 18 other SMCs producing news and current affairs commentary from a progressive and often partisan perspective. These BII fellows similarly produce BII-supported videos containing educational content on progressive policy issues and non-partisan electoral content, but it is far less anomalous from their regular content. Because most BII fellows' normal content is predominantly apolitical, we augmented this group with non-BII SMCs also producing political content from a progressive standpoint. The format of these SMCs' content varies from highly-polished programming akin to news broadcasts or late-night talk shows to SMCs talking from their homes into a camera about issues of the day. To capture the distinctive nature of modern SMCs, we selected SMCs who primarily became famous due to their social media accounts.[12] Like the apolitical progressive SMCs, this condition contains 20 SMCs generally producing less than 20 minutes of content a week and 5 SMCs producing longer-form content or a larger volume of content.

3.2.3 Placebo SMCs

To hold constant the encouragement to follow five new SMCs on social media, we compare the preceding treatment conditions with a placebo group. Our 20 shorter-form and five longer-form placebo SMCs are unified by producing entirely non-political content,[13] but otherwise cover an eclectic mix of topics in entertaining ways. Our placebo group includes SMCs specializing in comedy skits, food, travel, celebrity news, community exploration, lifestyle advice, animals, and musical covers. As with the preceding treatment conditions, we selected SMCs with similar followings and posting cadences; this group draws from and was inspired by applicants for the BII fellowship who

[12] This entailed excluding popular social media accounts hosted by politicians, journalists, and others with professional credibility outside social media. A couple of SMCs have appeared on TV programs, such as news shows or *The Bachelorette*, and in one case had run for office, but became famous for their online content.

[13] This was true at the point of selection before the study. Based on the content produced since, very few have ventured into political topics, even right around the election.

Table 2: SMC characteristics, by treatment condition

	Shorter-form SMCs			Longer-form SMCs		
	Apolitical	Political	Placebo	Apolitical	Political	Placebo
Panel A. Platform characteristics						
Produces content on Instagram	75%	45%	95%	60%	40%	100%
Produces content on TikTok	75%	65%	80%	60%	40%	80%
Produces content on YouTube	75%	30%	60%	100%	80%	80%
Mean followers on Instagram	542,867	262,577	702,444	447,433	266,500	452,620
Mean followers on TikTok	1,962,051	958,501	3,951,243	3,872,273	2,248,600	1,064,875
Mean followers on YouTube	680,599	64,466	3,465,091	1,165,050	1,621,750	1,827,500
Panel B. SMC characteristics						
Gender: Male	15%	35%	65%	20%	80%	40%
Age Group: 20s	25%	45%	35%	60%	0%	20%
Age Group: 30s	65%	35%	55%	20%	60%	60%
Age Group: 40s	0%	10%	10%	20%	40%	20%
LGBTQ+ / Ally	25%	25%	20%	40%	0%	0%
Ethnicity: Black	20%	35%	10%	0%	0%	40%
Ethnicity: Hispanic	5%	0%	10%	0%	0%	0%
Ethnicity: White	60%	55%	60%	80%	100%	40%
Panel C. SMC topics						
News	20%	100%	5%	0%	100%	0%
Lifestyle	80%	5%	80%	40%	0%	80%
Entertainment	35%	5%	75%	60%	0%	20%
Humor	15%	30%	40%	0%	40%	20%
Family	15%	0%	5%	0%	0%	20%
Money	0%	0%	0%	0%	0%	0%
Science	0%	0%	0%	20%	0%	0%
Environment	5%	0%	5%	20%	0%	0%
Culture	20%	0%	5%	40%	0%	0%
Education	20%	35%	25%	40%	20%	0%

Note: At the conclusion of the study period, we plan to provide a comprehensive summary of posting-level metadata for all SMCs included in the experiment. This analysis will describe the average weekly number of videos produced by SMCs, as well as the associated engagement metrics, such as the number of comments, likes, and shares. Our goal is to offer a representative snapshot of SMC activity and audience interaction over the five-month study period, highlighting key characteristics of the content and its engagement levels. Due to the nature of our data collection process, which involves gathering data all at once at the end of the study period, we will not be able to track time-series changes or observe trends in content creation and engagement over time. It is important to note that the availability and quality of the data may vary across platforms, given the differing levels of accessibility and technical restrictions associated with data gathering. These platform-specific constraints will inevitably influence the scope and depth of the data we can analyze.

were not selected.

3.2.4 Encouragements to consume content from assigned SMCs

While SMCs rely on producing engaging content for their livelihood, content appeal varies across audiences and asking participants to follow five SMCs is time-consuming. Our recommendation algorithm mitigates this by seeking to mimic the ways that social media algorithms and word-of-mouth naturally help to identify social media content of interest. However, to ensure high levels of

engagement with assigned SMCs for the purpose of evaluating their effects on consumers, we also provided two increasingly-artificial financial incentives.

First, we aimed to increase exposure to assigned content by incentivizing participants to follow or subscribe to a social media account for each assigned SMC. Toward the end of the baseline survey, and again within the midline survey, participants are offered $1 per SMC to upload a valid screenshot showing that they follow or subscribe to an assigned SMC.[14] Drawing inspiration from Levy's (2021) nudge to subscribe to news sites on Facebook, we expect this engagement will lead Instagram, TikTok, or YouTube's algorithms to show participants more content from this account in future.

Second, our most powerful but least natural encouragement rewards participants with $20 every two weeks for correctly answering questions about their five assigned SMCs. In each of our nine biweekly quizzes in Qualtrics, participants who correctly answer at least four of five multiple choice questions (one per assigned SMC) will receive $20 in credits on their survey platform.[15] To avoid informing participants through the quiz itself, questions avoid BII-supported content wherever possible and focus on non-political elements of SMC videos. This encouragement thus aims to expose participants to relevant content in preparing for the quiz or, ideally, because assigned SMCs are of genuine interest to them. Furthermore, to reduce attrition within this expensive category of participants, participants are informed that $5 of each quiz incentive won will be withheld until completion of the following midline or endline survey.

We equalize the maximum potential payment across participants in our study. All participants who do not receive the quiz encouragement will be entered into two lotteries, one conditional on completing the midline survey and the other conditional on completing the endline survey, with prizes that sum up to the maximum $180 incentive available to those in the quiz condition.[16]

3.2.5 Comparison groups

To understand the effects of progressively-minded SMC content, we employ three comparison groups. First, we compare the apolitical and political progressive SMC conditions with the placebo condition described above. This helps us to isolate the effect of exposure to different types of content on social media, holding the encouragement to use social media constant.

Second, we aim to hold the type of content constant, but vary whether its source is an SMC. To do so, we compare the two main SMC conditions with a group that is sent similar content via SMS and email at the same time as our quizzes every two weeks. This "newsletter" comprises five bullet

[14] Payments are made upon validation by the research team. Screenshots are deemed invalid if a participant is shown to have muted an assigned account. As part of a reminder of treatment assignment, we sent a follow-up message asking participants to again upload screenshots if they did not do so during the baseline survey.

[15] Each quiz is available for ten days and each question has four options. Similar financial incentives have achieved high and sustained compliance rates when encouraging study participants to watch CNN instead of Fox News (Broockman and Kalla forthcoming) as well as use VPNs to access foreign news in China (Chen and Yang 2019) and consume fact-checking podcasts in South Africa (Bowles et al. 2023).

[16] Both lotteries will yield $5 less in credits for winners receiving the algorithmic feedback condition that could yield $10 worth of credits for uploading validated screenshots.

Table 3: Distribution of panel survey participants by treatment and encouragement condition (targeted numbers in brackets)

		Treatment condition:				
		Apolitical progressive SMCs	Political progressive SMCs	Placebo SMCs	Messaging via SMS and email	Pure control
Encouragement type:	Recommendation only	366 [350]	364 [350]	365 [350]		
	\$1 per validated follow	360 [350]	361 [350]	362 [350]		
	Biweekly \$20 quiz	364 [350]	355 [350]	362 [350]		
	None				726 [700]	731 [700]

points that summarize in several sentences the information provided to BII fellows to form the basis of their videos. Although BII fellows choose which issues to emphasize, collaboration with the BII provides a rare opportunity to condition on the issues and perspectives SMCs draw from.

Third, we include a pure control condition that does not encourage participants to consume any content as part of the study. Relative to this group, our main SMC treatments are both likely to increase the use of social media and the type of content consumed on social media.

3.3 Randomization

The treatment and incentive conditions were cross-randomized to generate the intended distribution of participants shown in brackets in Table 3; the actual numbers assigned to each condition on our baseline survey are shown in each cell. Treatments were randomized within blocks of 13 participants with the same baseline political partisanship and who consumed similar levels of social media (above or below than 10 hours per week). These blocks were generated sequentially within Qualtrics, further enabling us to block treatment assignment by participants who completed the baseline survey around the same time.

3.4 Outcome measurement

Our outcomes will be drawn from the midline and endline surveys as well as several behavioral measures. We first validate whether treatment meaningfully altered social media consumption before turning to our immediate and downstream primary outcomes. Our baseline, midline, and (draft) endline survey instruments are included in the Appendix, while Table 5 specifies how our indicators are aggregated into inverse-covariance weighted indexes (Anderson 2008) to increase precision and mitigate multiple comparison issues.[17]

Given the importance of establishing the extent to which treatment induces engagement with

[17] As our pre-analysis plan specifies, we will apply the following protocols to address missingness in our outcome variables and covariates: (a) observations for which data are unobserved, due to survey attrition, refusal to answer questions, or unavailable administrative or audit records, will be treated as missing data and dropped from our analyses; (b) don't know survey responses will be assigned the median value on survey scales (except likelihood scales) and assigned zeros for binary or binarized variables (e.g. yes/no, correct/incorrect, etc. questions) and the lower end of the likelihood scales; and (c) where a question is not relevant to a respondent (e.g. because they did not vote), we assign zeros for binary or binarized variables and the lower end of likelihood scales. For index outcomes, we will drop respondents from an analysis when over half of an index's items are unobserved.

assigned SMCs' content and alters broader content exposure, we measure content consumption on Instagram, TikTok, and YouTube in several ways. First, our midline and endline surveys will elicit self-reported consumption of assigned SMCs at extensive and intensive margins by asking how frequently respondents encounter their content and the specific number of videos respondents recall watching on Instagram, TikTok, or YouTube; the control and SMS/email message groups will be asked about the SMCs they would have been recommended (in a randomly selected treatment condition). To address potential concerns about social desirability bias, we also measure the frequency of consuming unassigned SMCs from other treatment conditions and famous SMCs in general. Second, to behaviorally measure content internalization, our midline and endline surveys will further ask two factual questions about the content of videos produced by two assigned SMCs in the last few weeks. Like our quiz questions, these multiple choice questions will avoid politically-relevant content, but will not be incentivized. Third, we will ask participants to estimate the share of their social media content that contains news and politics and the share that is politically liberal. Finally, to measure actual consumption behaviors, we will track the YouTube videos watched by offering respondents $5 to upload their YouTube watch histories (79% reported being willing to do so in our pilot study) and scrape TikTok to log which accounts participants follow.[18]

To assess whether SMCs shape political engagement, policy priorities, and worldviews, we begin by considering the outcomes their content is most directly designed to influence. First, to capture broader political engagement, we ask three topical political knowledge questions (not related to BII-supported content) and how closely respondents report following politics. Second, to measure progressive policy attitudes relating to the BII's four core themes, we elicit policy preferences relating to curbing climate change, commitment to democracy, perceptions of corporate power, and support family leave, access to health insurance, and abortion. Third, we measure the salience of these four topic areas by eliciting the five most important policy issues for respondents (from a list of 14) and forcing them to prioritize between six policy priorities (with reducing immigration and improving schools alongside BII issues). Finally, to assess whether SMCs inculcate a progressive worldview more generally, we measure: (i) progressive perspectives on a broad array of policy issues; (ii) belief in progressive narratives that addressing major societal challenges requires systemic change, political transformation is needed to address long-running inequalities, government is needed to constrain free markets and special interests, and democracy requires an engaged citizenry; (iii) perceptions of respondents' individual, group, and generational political efficacy; and (iv) trust in electoral administration and experts (scientists, doctors, and journalists).

If SMCs' progressive content shapes these preferences and understandings, it may in turn induce a leftward shift in partisan attitudes and behaviors. To measure favorability toward political parties, we use 100-point feeling thermometers toward the Democrat and Republican parties, appraisal of Harris and Trump's economic policies, foreign policies, integrity, vision, and understanding of peo-

[18] Our ability to measure navigation data is constrained by what social media platforms provide. We are not aware of reliable ways to fully extract who Instagram users follow or what they consume.

ple like you, and presidential approval, trust in the president, and belief that the nation is moving in the right direction. We further measure electoral participation in terms of being registered to vote and whether a respondent intended to vote on election day or ultimately voted; to the extent possible, we will augment these survey responses with administrative turnout data. Turning to vote choice, we ask whether respondents intend to vote for Harris or have voted for Harris. Beyond electoral participation, we elicit self-reported engagement in various political activities and participation in protests for liberal causes. Moreover, to capture progressive priorities more behaviorally, our endline survey will offer participants the opportunity to donate one of 50 $100 lottery prizes to up to two conservative, neutral, and liberal causes. Finally, we examine faith in government institutions by eliciting trust in the President, Congress, Supreme Court, and election boards in addition to interpersonal trust.

3.5 Estimation

To test our main hypotheses, we examine differences between our two SMC conditions, non-SMC message condition, and various control groups. Our analyses of midline survey, endline survey, and administrative outcomes will restrict attention to participants who did not fail both attention checks in the corresponding survey. We will estimate sample average treatment effects (ATEs) of all treatment conditions in a given survey wave using OLS regressions of the following form:

$$Y_i = \alpha_b + \beta_0 Y_i^{pre} + \boldsymbol{\beta}_1[(Y_i^{pre} - \overline{Y}^{pre}) \times \mathbf{T}_i] + \boldsymbol{\gamma}\mathbf{X}_i + \boldsymbol{\tau}\mathbf{T}_i + \varepsilon_i, \quad (1)$$

where Y_i is an outcome (usually an index of outcomes) for respondent i, α_b is a randomization block fixed effect, Y_i^{pre} is the closest pre-treatment measure of the outcome (wherever possible) and $\overline{Y}^{pre}$ is its sample mean, $\mathbf{X}_i$ is a vector of pre-treatment covariates (and their demeaned interaction with treatment conditions) selected by the Belloni, Chernozhukov and Hansen (2014) double-LASSO selection procedure, and $\mathbf{T}_i$ is the vector of treatment assignments (with the pure control group serving as the omitted category).[19] In addition to analyzing each treatment $\times$ encouragement cell in Table 3 separately, better-powered analyses will pool across encouragement types using the following specification:

$$Y_i = \alpha_b + \beta_0 Y_i^{pre} + \boldsymbol{\beta}_1[(Y_i^{pre} - \overline{Y}^{pre}) \times \mathbf{T}_i] + \boldsymbol{\gamma}\mathbf{X}_i + \tau_A A_i + \tau_P P_i + \tau_O O_i + \tau_M M_i + \varepsilon_i, \quad (2)$$

where A_i is an indicator for the pooled progressive apolitical SMC condition, P_i is an indicator for the pooled progressive political SMC condition, O_i is an indicator for the pooled placebo SMC condition, and M_i is an indicator for the SMS and email messaging condition. In the event that the placebo conditions are indistinguishable from the pure control condition, we will combine these

[19] The demeaned covariate-by-treatment interaction terms are included to increase precision (Lin 2013). In the event of significant attrition, we will estimate specifications both with and without randomization block fixed effects (because differences in attrition across blocks would effectively alter observation weights).

Table 4: Minimum detectable effects (standardized) by estimand

	20% attrition				40% attrition			
	R^2=0.3		R^2=0.5		R^2=0.3		R^2=0.5	
	1-t	2-t	1-t	2-t	1-t	2-t	1-t	2-t
Equation (1): conditioning on a given SMC encouragement								
Apolitical/political progressive SMCs vs. pure control	0.15	0.17	0.13	0.15	0.18	0.20	0.15	0.17
Apolitical/political progressive SMCs vs. pure and placebo control	0.14	0.15	0.12	0.13	0.16	0.18	0.13	0.15
Apolitical/political progressive SMCs vs. Messaging via SMS and email	0.15	0.17	0.13	0.15	0.18	0.20	0.15	0.17
Difference between any two SMC conditions (including placebo control)	0.18	0.20	0.15	0.17	0.20	0.23	0.17	0.19
Equation (2): pooling across SMC encouragement types								
Apolitical/political progressive SMCs vs. pure control	0.11	0.13	0.10	0.11	0.13	0.15	0.11	0.12
Apolitical/political progressive SMCs vs. pure and placebo control	0.09	0.10	0.08	0.09	0.10	0.12	0.09	0.10
Apolitical/political progressive SMCs vs. Messaging via SMS and email	0.11	0.13	0.10	0.11	0.13	0.15	0.11	0.12
Difference between any two SMC conditions (including placebo control)	0.10	0.11	0.09	0.10	0.12	0.13	0.10	0.11

Notes: Each minimum detectable effect captures the smallest standardized effect that can be detected with statistical power of 0.8 and equal attrition across groups. 1-t and 2-t refer to one- and two-tailed tests.

groups as a larger control group in both specifications. Robust standard errors will be computed throughout, reflecting the individual-level randomization.

Given our large-sample randomization and the limited risk of spillovers between disparately-located panelists, these specifications can identify three principal estimands: (i) the ATE of any treatment $\times$ encouragement cell relative to the pure control group (given by $\hat{\boldsymbol{\tau}}$ in equation (1)); (ii) differences in the ATE between the apolitical progressive, political progressive, and placebo SMC conditions at any given encouragement (by testing for differences between elements of $\hat{\boldsymbol{\tau}}$ in equation (1)); and (iii) the ATEs and differences between ATEs when pooling across encouragements (given by $\hat{\tau}_A$, $\hat{\tau}_P$, and $\hat{\tau}_O$ in equation (2)).[20]

Our study is well-powered to detect these treatment effects. Table 4 reports standardized minimum detectable effects for our design under plausible attrition rates and levels of variance explained by predetermined covariates. Even for comparisons between just the quiz-incentivized SMC conditions (e.g. apolitical SMCs vs. placebo SMCs), the study is powered to detect relatively small effects of around 0.2 standard deviations; when pooling across encouragement types, we can detect differences of around 0.1 standard deviations. Such effect sizes are generally regarded as small.

The principal threat to identification is differential attrition. We will assess this by testing for differences in attrition rates across treatment conditions and examining covariate balance at every stage of analysis; the Belloni, Chernozhukov and Hansen (2014) LASSO procedure also mitigates effects of differential attrition by adjusting for correlates of treatment conditions. If differential attrition emerges, we will focus on subgroups where this is not a problem or, in a worst-case scenario, use bounding techniques.

Since our encouragements could struggle to generate exposure to assigned SMCs among some participants, intent to treat (ITT) estimates may not capture effects of exposure. To adjust for non-

[20] In addition to these sample ATEs, reweighting (by marginal distributions) will help us to generalize the results to a more representative group of young American adults in terms of gender, partisanship, age, and race/ethnicity.

compliance, we will use instrumental variable methods to rescale ITT estimates by the number of videos that a participant reports watching from their five assigned SMCs. Since binarizing a multi-valued treatment biases estimates when the instrument induces a first stage at multiple treatment intensities that affect the outcome (Marshall 2016), we will use 2SLS to estimate the complier-weighted average causal response for this effectively continuous endogenous treatment variable.

3.6 Hypotheses

We enumerate our main hypotheses in Table 5. For each hypothesis, we prespecify a corresponding index of outcomes; the items within families of outcomes will also be examined separately. The variable names in the table correspond with the survey question labels in our survey instruments.

Our "first stage" hypotheses (denoted by FS) pertain to participants' uptake of the intervention. Specifically, we anticipate that our encouragements to follow assigned SMCs (of all types) will increase engagement with assigned SMCs (hypothesis FS1), increase exposure to progressive and political content on social media in general (FS2), and decrease activity outside social media (FS3) relative to the messaging via SMS and email and pure control conditions. Observing substantial effects for FS1 is critical for the intervention to be informative about the impacts of SMCs, while FS2 and FS3 capture the indirect effects that help to understand the nature of treatment.

Our primary hypotheses (denoted by H) pertain to our main outcomes, positing that all treatment conditions except the placebo condition—but especially the apolitical and political progressive SMC treatment conditions—will increase political engagement (H1), progressive policy attitudes (H2), the salience of progressive policy issues (H3), progressive political perspectives (H4), favorability toward the Democratic party (H5) at the expense of the Republican party (H6), electoral participation (H7), electoral support for the Democratic party (H8), progressive non-electoral political behaviors (H9), and institutional and interpersonal trust (H10). We classify H1-H4 as the immediate outcomes most likely to be impacted by assignment to SMCs (or messaging via SMS and email), while H5-H10 are downstream outcomes only likely to change if the immediate outcomes are affected. While we expect SMC delivery to be more effective than biweekly summarizing messages sent via SMS and email, we do not have a clear expectation as to whether the apolitical or political SMCs will be more impactful, and thus do not register a directional hypothesis for this comparison. As noted above, political progressive SMCs communicate more political information but may turn respondents off or lack credibility, relative to apolitical progressive SMCs, due to their predominantly political content.

Our procedure for statistical inference is as follows. For the hypotheses where we register a directional expectation in the second column of Table 5, we will conduct one-tailed t tests. For hypotheses where no direction is prespecified (e.g. the difference between the apolitical and political conditions for most outcomes), as well as estimates in the opposite direction to our hypothesis, we will conduct two-tailed t tests. We will use the Benjamini and Hochberg (1995) method to adjust

Table 5: Hypotheses, tests, and outcome measurement

Hypothesis	Coefficient test	Midline survey outcome measures	Endline survey outcome measures	Administrative data measures
FIRST STAGE HYPOTHESES				
FS1: increased engagement with the content of assigned SMCs	$\{\tau_A, \tau_P, \tau_O\} > \tau_M = 0$	icw(following intensive margin items)	icw(following intensive margin items)	
FS1a: increased consumption of assigned SMCs' content (intensive margin)	$\{\tau_A, \tau_P, \tau_O\} > \tau_M = 0$	icw(mean(consump_freq_1_1, consump_freq_1_2, consump_freq_2_1, consump_freq_2_2, consump_freq_2_3), mean(consump_videos_1, consump_videos_2, consump_videos_3, consump_videos_4, consump_videos_5))	icw(mean(consump_freq_1_1, consump_freq_1_2, consump_freq_2_1, consump_freq_2_2, consump_freq_2_3), mean(consump_videos_1, consump_videos_2, consump_videos_3, consump_videos_4, consump_videos_5))	number of videos watched per assigned YouTube SMC
FS1b: increased consumption of assigned SMCs' content (extensive margin)	$\{\tau_A, \tau_P, \tau_O\} > \tau_M = 0$	mean(consump_freq_1_1>0, consump_freq_1_2>0, consump_freq_2_1>0, consump_freq_2_2>0, consump_freq_2_3>0, consump_videos_1>0, consump_videos_2>0, consump_videos_3>0, consump_videos_4>0, consump_videos_5>0)	mean(consump_freq_1_1>0, consump_freq_1_2>0, consump_freq_2_1>0, consump_freq_2_2>0, consump_freq_2_3>0, consump_videos_1>0, consump_videos_2>0, consump_videos_3>0, consump_videos_4>0, consump_videos_5>0)	share of assigned TikTok accounts followed; share of assigned YouTube accounts watched at least one video from
FS1c: increased knowledge of assigned SMCs' content	$\{\tau_A, \tau_P, \tau_O\} > \tau_M = 0$	mean(quiz_1=1, quiz_x=1)	mean(quiz_1=1, quiz_x=1)	
FS2: increased exposure to progressive and political content on social media in general	$\tau_P > \tau_O = 0, \tau_P > \{\tau_A, \tau_M\}$	icw(following items)	icw(following items)	
FS2a: increased exposure to news content on social media	$\tau_P > \tau_O = 0, \tau_P > \{\tau_A, \tau_M\}$	sm_content_1 * (media_facebook + media_instagram + media_tiktok + media_youtube)	sm_content_1 * (media_facebook + media_instagram + media_tiktok + media_youtube)	
FS2b: increased share of news and political content on social media	$\tau_P > \tau_O = 0, \tau_P > \{\tau_A, \tau_M\}$	mean(sm_content_1, sm_content_2)	mean(sm_content_1, sm_content_2)	
FS2c: increased share of liberal political content on social media	$\tau_P > \tau_O = 0, \tau_P > \{\tau_A, \tau_M\}$	sm_content_2 * sm_liberal_lean (recoding don't know as balanced)	sm_content_2 * sm_liberal_lean (recoding don't know as balanced)	
FS3: decreased activity outside social media	$\{\tau_A, \tau_P, \tau_O\} < \tau_M = 0$	icw(following items)	icw(following items)	
FS3a: decreased consumption of traditional media	$\{\tau_A, \tau_P, \tau_O\} < \tau_M = 0$	media_tv + media_radio	media_tv + media_radio	
FS3b: decreased engagement in offline activities	$\{\tau_A, \tau_P, \tau_O\} < \tau_M = 0$	count(activities)	count(activities)	
IMMEDIATE OUTCOME HYPOTHESES				
H1: increased political engagement in general	$\tau_P > \{\tau_A, \tau_M\} > \tau_O = 0$	icw(following items)	icw(following items)	
H1a: increased knowledge of current affairs	$\tau_P > \{\tau_A, \tau_M\} > \tau_O = 0$	mean(pol_know_1=1, pol_know_2=1, pol_know_3=1)	mean(pol_know_1=1, pol_know_2=1, pol_know_3=1)	
H1b: increased interest in politics	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	follow_politics	follow_politics	
H2: increased progressive policy attitudes	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(following items)	icw(following items)	
H2a: increased progressive climate preferences	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	policy_environment	policy_environment	
H2b: increased progressive democracy preferences	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(democracy, agree_violence_unjustified)	mean(democracy, agree_violence_unjustified)	
H2c: increased progressive economic justice preferences	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(policy_corporate_power, -policy_free_markets)	mean(policy_corporate_power, -policy_free_markets)	
H2d: increased progressive public health preferences	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(policy_family, health_insurance, abortion)	mean(policy_family, health_insurance, abortion, **vax_importance**)	
H3: increased concern for progressive policy issues	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(following items)	icw(following items)	
H3a: increased salience of climate issues	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(salient_issues=12, policy_salience_3)	mean(salient_issues=12, policy_salience_3)	
H3b: increased salience of democracy issues	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(salient_issues=11, policy_salience_2)	mean(salient_issues=11, policy_salience_2)	
H3c: increased salience of economic justice issues	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(salient_issues=(5 or 6), policy_salience_1)	mean(salient_issues=(5 or 6), policy_salience_1)	
H3d: increased salience of public health issues	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(salient_issues=(1 or 7), policy_salience_4)	mean(salient_issues=(1 or 7), policy_salience_4)	
H4: increased progressive political perspective	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(following items)	icw(following items)	
H4a: increased progressive policy preferences in general	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(policy_environment, policy_family, policy_corporate_power, racial_inequality, health_insurance, abortion, -policy_free_markets, -policy_cut_taxes)	icw(policy_environment, policy_family, policy_corporate_power, racial_inequality, health_insurance, abortion, -policy_free_markets, -policy_cut_taxes, **vax_importance**)	
H4b: increased progressive worldview	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(prog_worldview_systemic, prog_worldview_government, prog_worldview_inequalities, prog_worldview_participation)	mean(prog_worldview_systemic, prog_worldview_government, prog_worldview_inequalities, prog_worldview_participation)	
H4c: increased individual and group political efficacy	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(ind_efficacy, coll_efficacy, young_generations_power)	mean(ind_efficacy, coll_efficacy, young_generations_power)	
H4d: increased trust in the system of electoral administration and experts	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(agree_elections_fair, trust_election_boards, trust_scientists, trust_doctors, trust_journalists)	icw(agree_elections_fair, trust_election_boards, trust_scientists, trust_doctors, trust_journalists)	

Notes: Coefficients refer to the pooled estimating equations above, but similar predictions hold for each encouragement group within a treatment category. "icw" denotes an inverse covariance weighting function with variables as its arguments; "mean" denotes a mean function with variables as its arguments; "count" denotes a function counting the number of items selected from a variable; "abs" denotes the absolute value function. Emboldened variable names denote variables measured in only the midline or only the endline survey.

Table 5: Hypotheses, tests, and outcome measurement (continued)

Hypothesis	Coefficient test	Midline survey outcome measures	Endline survey outcome measures	Administrative data measures
DOWNSTREAM OUTCOME HYPOTHESES				
H5: increased favorability toward Democrats	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(following items)	icw(following items)	
H5a: increased feeling toward the Democratic party	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	party_affection_1	party_affection_1	
H5b: increased appraisal of Kamala Harris as presidential candidate	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	mean(attributes_harris_economics, attributes_harris_foreign, attributes_harris_trust, attributes_harris_vision, attributes_harris_understands)	mean(attributes_harris_economics, attributes_harris_foreign, attributes_harris_trust, attributes_harris_vision, attributes_harris_understands)	
H5c: increased appraisal of incumbent government performance	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(**nation_direction**, biden_approval, trust_president)	icw(biden_approval, trust_president)	
H6: decreased favorability toward Republicans	$\{\tau_A, \tau_P\} < \tau_M < \tau_O = 0$	icw(following items)	icw(following items)	
H6a: decreased feeling toward the Republican party	$\{\tau_A, \tau_P\} < \tau_M < \tau_O = 0$	party_affection_2	party_affection_2	
H6b: decreased appraisal of Donald Trump as presidential candidate	$\{\tau_A, \tau_P\} < \tau_M < \tau_O = 0$	mean(attributes_trump_economics, attributes_trump_foreign, attributes_trump_trust, attributes_trump_vision, attributes_trump_understands)	mean(attributes_trump_economics, attributes_trump_foreign, attributes_trump_trust, attributes_trump_vision, attributes_trump_understands)	
H7: increased electoral participation	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(following items)		
H7a: increased probability of being registered to vote	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	**registered_to_vote**=1		validated registration data (if possible)
H7b: increased probability of turning out to vote	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	**turnout**$\geq$3	mean(**turnout_pres**=1, **turnout_house**=1, **turnout_senate**=1)	validated turnout data (if possible)
H8: increased probability of voting Democrat	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$		icw(following items)	
H8a: increase probability of voting for Kamala Harris for president	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	**vote_choice**=1 or **vote_choice_early**=1	**vote_choice_pres**=1	
H8b: increase probability of voting Democrat for House	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$		**vote_choice_house**=1	
H8c: increase probability of voting Democrat for Senate	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$		**vote_choice_senate**=1	
H9: increased non-electoral participation	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	icw(following items)	icw(following items)	
H9a: increased probability of non-electoral political action	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	count(non_election_part)	count(non_election_part)	
H9b: increased probability of participating in a protest for a liberal cause	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$	(non_election_part=1 and protest_issue=3)	(non_election_part=1 and protest_issue=3)	
H9c: increased probability of hypothetically resisting Trump administration	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$		**trump_policy_react**=(1 or 2 or 3)	
H9d: increased probability of donating to a liberal cause	$\{\tau_A, \tau_P\} > \tau_M > \tau_O = 0$		**donation**=(1 or 3)	
H10: predominantly apolitical SMCs are more likely to increase trust		icw(following items)	icw(following items)	
H10a: predominantly apolitical SMCs increased institutional trust in government relative to predominantly political SMCs	$\tau_A > \tau_M > \tau_P$	mean(trust_president, trust_congress, trust_supreme_court, trust_election_boards)	mean(trust_president, trust_congress, trust_supreme_court, trust_election_boards)	
H10b: predominantly apolitical SMCs increased interpersonal trust relative to predominantly political SMCs	$\tau_A > \tau_M > \tau_P$	agree_trust_people	agree_trust_people	

Notes: Coefficients refer to the pooled estimating equations above, but similar predictions hold for each encouragement group within a treatment category. "icw" denotes an inverse covariance weighting function with variables as its arguments; "mean" denotes a mean function with variables as its arguments; "count" denotes a function counting the number of items selected from a variable; "abs" denotes the absolute value function. Emboldened variable names denote variables measured in only the midline or only the endline survey.

p-values for multiple comparisons across our primary hypothesis indices and treatment groups.

We will also examine effects on secondary outcomes of potential interest, but treat these analyses as exploratory. Secondary outcomes, with the variable names from the midline and endline surveys in the Appendix, include:

- Continuing to follow assigned SMCs (`follow_after_rec_...` and `quiz_post`);
- Perceptions of government responsiveness (`pols_responsive`);
- Affective and policy political polarization (abs(`party_affection_1` - `party_affection_2`), abs(`support_affection_1` - `support_affection_2`), and abs(icw(`policy_environment`, `policy_family`, `policy_corporate_power`, `racial_inequality`, `health_insurance`, `abortion`, -`policy_free_markets`, -`policy_cut_taxes`, `vax_importance`)));
- Health care uptake (`vaccinations` and `aca_enrollment`);
- Mental health (mean(`mental_health_happy`, -`mental_health_depressed`, -`mental_health_anxious`, `mental_health_worthwhile`, `mental_health_bored`));
- Attitudes toward social media platform regulations (mean(-`platform_policy_intervene`, `platform_policy_accountable`)); and
- Perceived social media value (mean(`sm_good_you`, `sm_good_society`)).

4 Results [simulated example, results to be added]

For the purposes of this registered design, Table 6 provides simulated results for hypothesis H1 to illustrate how we expect to report our results. The outcome data are randomly generated and assume that there is no attrition from baseline; consequently, the R^2 should be significantly higher for our actual data. We will also present key results graphically, wherever possible.

5 Potential mechanisms [results to be added]

Exploratory analyses will further investigate the possible mechanisms driving any effects of starting to follow assigned SMCs. In terms of mediators for primary and secondary outcomes, we will examine the perceived appeal of these SMCs' content and the connection participants feel towards these SMCs among treated participants (`smi_overall_rating_...`, `smi_connected_...`, `smi_interesting_...`, `smi_informative_...`, `smi_trustworthy_...`), trust in SMCs (`trust_smis`), and reliance on social media for acquiring political information (`seek_pol_info`=7).

Regarding moderators, we will consider both factors that amplify the impact of exposure to new SMCs' content and factors shaping its impact upon exposure. In terms of amplifying exposure, we will examine heterogeneity by baseline weekly hours of social media use (`media_instagram` +

Table 6: Effects of SMCs on political engagement [simulated outcome data]

	Midline survey outcomes						*Endline survey outcomes*					
	Political engagement index		**Knowledge of current affairs**		**Follow politics**		**Political engagement index**		**Knowledge of current affairs**		**Follow politics**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All treatment conditions separately												
Apolitical SMCs (quiz)	0.022	0.017	-0.009	-0.013	0.067	0.078	0.118*	0.121*	0.049***	0.042**	-0.011	0.014
	(0.066)	(0.070)	(0.019)	(0.020)	(0.072)	(0.077)	(0.067)	(0.071)	(0.019)	(0.020)	(0.074)	(0.078)
Apolitical SMCs (follow)	-0.026	-0.019	0.001	0.003	-0.045	-0.051	0.022	0.069	0.019	0.038*	-0.041	-0.048
	(0.066)	(0.068)	(0.019)	(0.020)	(0.071)	(0.075)	(0.067)	(0.070)	(0.018)	(0.019)	(0.075)	(0.076)
Apolitical SMCs (recommendation)	0.017	0.006	0.004	-0.004	0.012	0.024	0.064	0.078	-0.000	0.008	0.099	0.086
	(0.064)	(0.068)	(0.019)	(0.020)	(0.072)	(0.075)	(0.065)	(0.070)	(0.018)	(0.019)	(0.072)	(0.076)
Political SMCs (quiz)	-0.078	-0.104	-0.013	-0.014	-0.071	-0.108	-0.039	-0.098	-0.013	-0.024	-0.007	-0.047
	(0.067)	(0.068)	(0.019)	(0.020)	(0.073)	(0.076)	(0.067)	(0.070)	(0.018)	(0.020)	(0.073)	(0.076)
Political SMCs (follow)	-0.069	-0.039	-0.011	-0.010	-0.065	-0.027	0.137**	0.098	0.034*	0.025	0.076	0.047
	(0.063)	(0.070)	(0.019)	(0.020)	(0.071)	(0.078)	(0.065)	(0.072)	(0.018)	(0.020)	(0.071)	(0.079)
Political SMCs (recommendation)	-0.080	-0.035	-0.010	-0.006	-0.084	-0.033	0.049	0.039	0.030*	0.031	-0.042	-0.058
	(0.064)	(0.067)	(0.018)	(0.019)	(0.075)	(0.075)	(0.065)	(0.069)	(0.018)	(0.019)	(0.071)	(0.075)
Placebo SMCs (quiz)	-0.010	0.048	-0.015	-0.008	0.041	0.108	0.137**	0.124*	0.036*	0.032*	0.071	0.072
	(0.067)	(0.067)	(0.019)	(0.019)	(0.071)	(0.074)	(0.069)	(0.069)	(0.019)	(0.019)	(0.072)	(0.075)
Placebo SMCs (follow)	0.019	0.024	-0.008	-0.007	0.058	0.066	0.059	0.087	0.017	0.019	0.024	0.053
	(0.065)	(0.066)	(0.019)	(0.019)	(0.071)	(0.073)	(0.066)	(0.068)	(0.019)	(0.019)	(0.074)	(0.074)
Placebo SMCs (recommendation)	0.098	0.102	-0.007	-0.011	0.179**	0.199***	0.075	0.124*	0.032*	0.036*	-0.009	0.048
	(0.066)	(0.067)	(0.019)	(0.019)	(0.073)	(0.074)	(0.067)	(0.068)	(0.019)	(0.019)	(0.071)	(0.074)
SMS/email message	-0.065	-0.062	-0.031**	-0.031**	0.016	0.023	0.082	0.083	0.024	0.030*	0.030	0.010
	(0.053)	(0.053)	(0.015)	(0.015)	(0.058)	(0.059)	(0.054)	(0.055)	(0.015)	(0.015)	(0.059)	(0.060)
Apolitical SMCs (quiz) - Placebo SMCs (quiz)	0.032	-0.031	0.006	-0.005	0.026	-0.030	-0.019	-0.002	0.013	0.010	-0.082	-0.058
	(0.078)	(0.08)	(0.022)	(0.023)	(0.082)	(0.089)	(0.08)	(0.083)	(0.022)	(0.023)	(0.085)	(0.09)
Political SMCs (quiz) - Placebo SMCs (quiz)	-0.068	-0.152	0.002	-0.006	-0.112	-0.216	-0.176	-0.222	-0.049	-0.056	-0.078	-0.119
	(0.079)	(0.079)	(0.022)	(0.023)	(0.083)	(0.088)	(0.08)	(0.082)	(0.021)	(0.023)	(0.084)	(0.089)
Apolitical SMCs (quiz) - Political SMCs (quiz)	0.100	0.121	0.005	0.000	0.138	0.186	0.157	0.220	0.063	0.066	-0.004	0.061
	(0.078)	(0.082)	(0.022)	(0.024)	(0.084)	(0.09)	(0.079)	(0.084)	(0.021)	(0.023)	(0.086)	(0.091)
Apolitical SMCs (quiz) - SMS/email message	0.087	0.079	0.022	0.018	0.051	0.055	0.036	0.039	0.025	0.012	-0.041	0.003
	(0.067)	(0.07)	(0.019)	(0.02)	(0.072)	(0.077)	(0.068)	(0.071)	(0.019)	(0.02)	(0.075)	(0.078)
Political SMCs (quiz) - SMS/email message	-0.013	-0.042	0.018	0.017	-0.087	-0.131	-0.121	-0.181	-0.038	-0.054	-0.037	-0.057
	(0.067)	(0.068)	(0.018)	(0.02)	(0.073)	(0.075)	(0.068)	(0.07)	(0.018)	(0.02)	(0.074)	(0.076)
R^2	0.07		0.08		0.07		0.07		0.08		0.07	
Number of LASSO-selected covariates		840		840		840		840		840		840
Panel B: Pooling across encouragements												
Apolitical SMCs (pooled)	0.004	-0.003	-0.001	-0.005	0.011	0.012	0.068	0.093*	0.022	0.030**	0.016	0.026
	(0.048)	(0.050)	(0.014)	(0.014)	(0.053)	(0.055)	(0.049)	(0.051)	(0.014)	(0.014)	(0.054)	(0.056)
Political SMCs (pooled)	-0.076	-0.062	-0.012	-0.012	-0.074	-0.053	0.049	0.037	0.017	0.017	0.009	-0.009
	(0.048)	(0.050)	(0.014)	(0.014)	(0.054)	(0.055)	(0.049)	(0.051)	(0.014)	(0.014)	(0.053)	(0.055)
Placebo SMCs (pooled)	0.036	0.058	-0.010	-0.010	0.092*	0.128**	0.090*	0.108**	0.028**	0.030**	0.027	0.048
	(0.049)	(0.050)	(0.014)	(0.014)	(0.053)	(0.055)	(0.050)	(0.051)	(0.014)	(0.014)	(0.054)	(0.055)
SMS/email message	-0.065	-0.062	-0.031**	-0.034**	0.016	0.026	0.081	0.083	0.024	0.031**	0.030	0.011
	(0.053)	(0.054)	(0.015)	(0.016)	(0.058)	(0.060)	(0.054)	(0.056)	(0.015)	(0.015)	(0.059)	(0.060)
Apolitical SMCs (pooled) - Placebo SMCs (pooled)	-0.032	-0.060	0.008	0.005	-0.082	-0.116	-0.022	-0.015	-0.006	-0.000	-0.011	-0.022
	(0.044)	(0.045)	(0.013)	(0.013)	(0.048)	(0.049)	(0.045)	(0.046)	(0.012)	(0.013)	(0.049)	(0.05)
Political SMCs (pooled) - Placebo SMCs (pooled)	-0.112	-0.120	-0.002	-0.002	-0.166	-0.181	-0.041	-0.071	-0.011	-0.013	-0.019	-0.057
	(0.044)	(0.045)	(0.012)	(0.013)	(0.048)	(0.049)	(0.045)	(0.046)	(0.012)	(0.013)	(0.048)	(0.05)
Apolitical SMCs (pooled) - Political SMCs (pooled)	-0.080	-0.060	-0.010	-0.007	-0.085	-0.065	-0.018	-0.056	-0.005	-0.013	-0.008	-0.035
	(0.043)	(0.045)	(0.013)	(0.013)	(0.048)	(0.05)	(0.044)	(0.046)	(0.012)	(0.013)	(0.049)	(0.05)
Apolitical SMCs (pooled) - SMS/email message	0.069	0.059	0.030	0.029	-0.005	-0.014	-0.014	0.010	-0.002	-0.001	-0.013	0.015
	(0.049)	(0.05)	(0.014)	(0.014)	(0.053)	(0.055)	(0.05)	(0.051)	(0.014)	(0.014)	(0.055)	(0.056)
Political SMCs (pooled) - SMS/email message	-0.011	-0.001	0.019	0.022	-0.090	-0.078	-0.032	-0.046	-0.007	-0.014	-0.021	-0.020
	(0.049)	(0.05)	(0.014)	(0.014)	(0.054)	(0.055)	(0.05)	(0.051)	(0.014)	(0.014)	(0.054)	(0.055)
R^2	0.07		0.08		0.07		0.07		0.08		0.07	
Number of LASSO-selected covariates		420		420		420		420		420		420
Observations	4,716	4,169	4,716	4,169	4,716	4,169	4,716	4,169	4,716	4,169	4,716	4,169
Control outcome mean	-0.00	-0.01	0.51	0.51	2.49	2.47	-0.00	-0.01	0.49	0.48	2.47	2.47
Control outcome standard deviation	1.00	0.99	0.30	0.30	1.10	1.10	1.00	1.00	0.29	0.29	1.10	1.09

Notes: Each specification is estimated using OLS, and includes randomization block fixed effects and adjusts for lagged outcomes and their (demeaned) interaction with each treatment condition; these covariate coefficients are omitted, but will be included in the Appendix for the full submission. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

`media_tiktok` + `media_youtube`), baseline preference for political social media content (`sm_content_prefs`), baseline resistance to political content (`smi_politics`), and baseline openness to following new SMCs (`smi_open`). These analyses will be exploratory because these moderators could operate in

either direction.

In terms of amplifying persuasion, we will examine how treatment effects vary with measures of the participant's prior beliefs and their perceptions of the signal generating likelihood function. First, we test whether proxies for the strength of prior beliefs (`follow_politics` and `media_instagram` + `media_tiktok` + `media_youtube`) reduce the effects of treatment. Second, we will assess whether more progressive prior positions (measured using the pre-treatment measure of relevant outcomes as well as prior partisanship and `vote_choice`) make participants more responsive to treatment (in line with theories of motivated reasoning) or less responsive to treatment (in line with theories of Bayesian learning). Finally, we examine whether proxies for the credibility of the SMC (`smi_connected` and the participant being a Democrat partisan) increase the effect of treatment.

6 Discussion [to be updated based on results]

This study will provide the first large-scale and long-term field experimental evidence of the political consequences of sustained exposure to previously-unfollowed SMCs. Over five months during and after the 2024 U.S. Presidential election campaign, we encourage treated individuals to consume five progressively-minded SMCs, varying whether these SMCs' content is primarily political or apolitical. Measuring a wide array of attitudinal and behavioral outcomes, our findings will take a significant step toward understanding how different kinds of digital intermediaries can engage and influence younger generations in today' post-broadcast democracy. The results will thus have implications for reengaging younger voters and understanding public opinion in the multifocal digital media age, the communication strategies of election campaigns and policy organizations, and the potential regulation of political content on social media.

Our study design is not without trade-offs and limitations that could define the frontier for future research and help explain null findings. First, our experiment encourages participants to follow SMCs of potential interest they did not already follow. We thus capture the effects of efforts to establish a connection with assigned SMCs over five months, rather than the effects of SMCs that participants opted to follow and are already somewhat connected to. Consequently, our findings may understate the effects of the SMCs with whom users have developed the strongest para-social relationships. Nevertheless, users regularly encounter new SMCs on social media, whether through algorithmic or interpersonal recommendations, so understanding the impact and the potential to develop ties with new SMCs may be just as important. Future studies evaluating the effect of messaging by SMCs an individual already follows would likely require recruiting followers from participating SMCs and then working with SMCs to randomize content across SMCs or randomly segment follower audiences to receive different content.

Second, the overall treatment intensity is a modest fraction of the several hours of social media content our average participant consumes daily. Treated participants are encouraged to follow five

SMCs for five months, which may underestimate the cumulative effects of exclusively consuming these SMCs' content over time. However, the other content social media users consume is often apolitical, while our intervention may induce users to seek out and platform algorithms to present other progressive content (Levy 2021). As such, without altering platforms' proprietary algorithms to more fundamentally shape what users consume (Guess et al. 2023), our intervention is likely to be at least as powerful as alternative external efforts to alter the SMCs an individual consumes.

Third, our focus on progressive, policy-focused content may not generalize to other types of SMC messaging. For instance, right-wing conspiracy theories or emotionally charged narratives—instead of policy and fact-oriented content—could generate entirely different effects, potentially amplified by their reliance on sensationalism or fear-based appeals. As organizations across the political spectrum increasingly adopt SMC-driven strategies, particularly when out of power and lacking other channels of influence, understanding the impact of varied content styles remains an important area for future research.

Fourth, our sample of younger generations is both a strength and a limitation. Individuals under 45 are more likely than older generations to engage with SMCs, making them an ideal group for studying this phenomenon. However, this focus means our findings may not necessarily generalize to older populations who may have distinct social media preferences. As older individuals increasingly adopt social media platforms, it will be interesting to test whether lower digital literacy and less familiarity with social media among older generations might paradoxically make SMCs even more impactful upon exposure (Guess, Nagler and Tucker 2019; Guess and Munger 2023; Lyons, Montgomery and Refiler 2024).

Finally, the timing of the study during the 2024 U.S. presidential campaign—a high-stakes, media-saturated period, with numerous competing influences—may have amplified or undermined the visibility and impact of SMCs. Moreover, some social media platforms modified their political promotion rules to downweight political content in their algorithms during the campaign, which in turn altered the content of SMCs seeking engagement. As a result, the observed effect sizes might not fully represent the typical influence of SMCs during less politically charged times. Nonetheless, the election underscored the growing prominence of non-traditional social media figures in American democracy. From Trump's acknowledgment of figures like Adin Ross and Bussin' With The Boys in his victory speech to Kamala Harris's appearance on *Call Her Daddy*, 2024 highlighted how creators who built their reputations outside traditional political channels are becoming central to campaign strategies. These examples reinforce the relevance of our findings, even if the electoral context shaped the magnitude of observed effects.

Ultimately, our study situates itself within a moment of profound change in whether and how citizens consume political information. Growing evidence of news avoidance and political apathy signal a fundamental challenge for civic capacity: how to keep citizens engaged in a media environment where opting out of politics is easier than ever. The rise of alternative intermediaries

like SMCs offers one important pathway. Still, it raises profound questions about the resilience of democratic discourse in a world where the lines between information, news, and entertainment blur. Our evidence will not resolve these tensions, but underscores the urgency of addressing them in an era where the allure of infinite entertainment fragments our attention—where screens grow larger, images sharper, and videos shorter, distilling complex ideas into moments seamlessly woven into endless scrolls. These seemingly micro-narratives can nevertheless profoundly reshape the macro contours of political communication.

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A Online appendix

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A.1 Research ethics

Beyond receiving IRB approval, the design of our intervention reflected careful attention to the ethics of field experimentation and associated data collection consistent with APSA's *Principles and Guidance for Human Subjects Research*. Below, we outline the considerations and measures taken to ensure that our field experiment is ethical and aligned with established principles in the social science.

First, participants in this study were encouraged, not forced, to follow SMCs without deception. All participants provided informed consent before the study began, understanding that their participation—including the possibility of being asked to follow new SMCs—was voluntary and that they could withdraw from the study at any time without penalty. Our encouragements to follow new accounts mirror the recommendations participants encounter organically in their daily lives on platforms such as Instagram, TikTok, and YouTube and via friends. The additional provision of financial incentives to consume media content for some participants is a common approach in the literature to ensure high levels of treatment exposure (e.g. Bowles et al. 2023; Broockman and Kalla forthcoming; Chen and Yang 2019).

Second, the study's SMC recommendations were tailored to match participants' interests and preferences, as determined through a baseline survey and the machine learning matching algorithm described in Section A.2. This not only increased the likelihood that participants would enjoy the suggested content but also reduced any perception of manipulation or undue pressure. Since treated participants could choose not to consume the content we suggested or (in case of the SMS/email message treatment) sent to them, our expectation was that participants would not be harmed—and would likely benefit—from participating in the study.

Third, participants received appropriate compensation for their time completing surveys, with payment levels designed to be fair and non-coercive. In particular, participants were paid $3.43 in survey platform credits for completing the baseline survey and $5.40 for completing the midline survey, and will be offered $5.40 for completing the endline survey; additional incentives are provided for participants who are slow to respond to surveys.

Fourth, quota sampling ensured that our participant pool was diverse and broadly representative of younger American adults aged 18–45 in terms of gender, age, education, and partisan identification. Efforts were also made to exclude individuals who are not aligned with the study's focus, namely those who infrequently use Instagram, TikTok, or YouTube. This approach ensured that participants could engage meaningfully with the study while minimizing unnecessary burden on individuals outside the intended scope.

Fifth, all collected data were anonymized and securely stored to safeguard participants' privacy. We also collected some personally identifiable information—such as social media account details and corresponding platform-level engagement data—to verify participants' social media user status and engagement beyond survey responses, which participants were informed about before starting the study. The endline survey will also offer participants the voluntary opportunity to share their YouTube watch histories; they will be offered $5 additional credits to do so.

Finally, the small scale of the randomized intervention and the geographic dispersion of study participants across the U.S. ensures that the intervention could not plausibly have influenced 2024 election outcomes.

A.2 Matching algorithm

Our approach to recommending participants for the main survey consists of three steps. First, we characterized the content of all SMCs in our treatment and placebo groups. Second, we collected data on SMC preferences using a 'cold-start' matching approach in a pilot study, where we sought to match participants to SMCs (within their treatment condition) based on a distance metric based on the research team's initial assumptions about user preferences for SMCs. Third, based on the pilot data, we developed a recommendation system using machine learning techniques to refine the matching algorithm. Below, we describe each step in detail for building the matching algorithm for the main study.

A.2.1 Characterizing the content of creators

Recommendation algorithms generally benefit from content characterization (Javed et al. 2021). Following this best practice, we initially characterized the content of all SMCs in the apolitical, political, and placebo groups by manually coding the set of characteristics in accordance with a predefined coding scheme.

Each member of the research team independently coded the following characteristics of creators: gender, sexual orientation, ethnicity, age group, ideology, and expertise. We also assessed the content's visual aspects (e.g. fashionable, polished), verbal style (e.g. formal, assertive), whether the content was political, and its primary topics (e.g. news, lifestyle, entertainment, humor, family, money, science, environment, culture, education). Additionally, we coded whether the content might be perceived as polarizing by social media users. When possible, we relied on account descriptions written by the creators themselves or publicly available information online; if these sources were insufficient, we made judgments based on our own assessments.

A.2.2 Gathering the data on individual preferences

A common challenge in developing recommendation algorithms, known as the cold start problem (Park and Chu 2009), is the lack of data on user-item interactions. This often requires initially launching the model by mapping users to items using heuristics that predict which types of content users with certain characteristics might prefer. In our application, we addressed this issue by utilizing a pilot containing 278 participants to enhance the recommendation system.

In our pilot survey, we measured various characteristics of our participants, including age, gender, education, sexual orientation, income, race, parental status, political ideology, and engagement with politics. We also assessed whether participants follow creators, to what extent they feel connected to them, and their openness to following new creators, including political ones. Additionally, we asked participants how much they value the visual (e.g. fashionable, polished) and verbal (e.g. formal, assertive) aspects of creators' content, as well as the importance of specific content elements, such as topic, content quality, visual and verbal style, and characteristics of creators (race, popularity, gender, sexuality, age, ideology, and expertise). We also gathered information on topics of interest (e.g. news, lifestyle, entertainment, humor, family, money, science, environment, culture, and education) and how participants discover new creators (e.g. searching the platform or asking friends).

Based on these characteristics, our pilot study calculated a simple distance metric that compared participant preferences (weighted by the importance of each aspect) with creator demographics and content characteristics. We evaluated the performance of this cold-start matching algorithm by asking participants about their overall satisfaction with the content of assigned creators on a 1-

10 scale ($\mu = 6.13$, $SD = 2.47$), the extent to which they engaged with the content of assigned creators on a 1-4 scale ($\mu = 0.75$, $SD = 0.99$), and whether they would continue following the assigned creators after the study on a 1-5 scale ($\mu = 3.25$, $SD = 1.36$). The resulting metrics were standardized and aggregated into an index using Principal Components Analysis (PCA), which we then used to inform the recommendation system for the main study.

A.2.3 Building the recommendation system

The most common approaches to recommendation systems typically involve processing either user characteristics or content characteristics, known respectively as collaborative filtering (Sarwar et al. 2001) and content-based filtering (Pazzani 1999). In either approach, the general framework is to leverage available data to generate personalized recommendations. Since we obtained characteristics on both individual preferences (in our baseline survey), creator attributes (hand-coded by the research team), and various metrics of user engagement with creators in the cold-start setup, we developed our approach using the hybrid recommendation system framework (He et al. 2017).

The hybrid approach to recommendation systems benefits from integrating multiple types of information, enabling it to provide more accurate recommendations (Burke 2002). First, it addresses the cold start problem associated with limited data by integrating both user and content attributes to generate initial recommendations with limited user interaction data. This was a key advantage in our application, as we expanded the list of creators recommended in the main study beyond the pilot, meaning we lacked data on user interactions with newly added creators. Second, the hybrid approach reduces over-specialization and aims to provide more diverse recommendations, which was particularly valuable in our application given the variety of topics and creator styles within the pool of SMCs selected for the main study.

Our hybrid recommendation system is based on a neural collaborative filtering approach (He et al. 2017). Our model architecture takes two sparse input vectors: one representing the participant (including relevant participant characteristics) and the other representing the creators. These inputs pass through embedding layers that convert the sparse data into dense, latent vectors. The latent vectors are then fed into a multi-layer neural network that maps them to predicted probability scores, allowing the model to learn complex participant-creator relationships from the data.

First, two embedding layers were used to map participant and creator IDs to dense vector representations of 200 latent factors. The flattened and concatenated embedding vectors were passed through dense layers with Batch Normalization, LeakyReLU activation, and Dropout for regularization, progressively reducing the dimensions from 128 to 64 to 32. These layers captured interactions between participant-creator embeddings and participant-characteristic data, adding non-linearity to the model. The final output is a single prediction, generated using a linear activation. The model architecture is presented in Figure A.1.

We trained the model using early stopping to prevent overfitting. Early stopping monitored the validation loss during training, halting the process when no further improvement was observed. In this training process, the model converged in 21 epochs, achieving stable performance on the validation set before reaching the maximum of 100 epochs. The resulting model performed well on both train and test samples, leaving no signs of overfitting. The matching algorithm performance is summarized in Figure A.2: the model achieved an MSE of 0.80, MAE of 0.66, RMSE of 0.89, and an R^2 of 0.59 on the test sample, indicating moderate predictive accuracy.

Figure A.1: Neural collaborative filtering model architecture

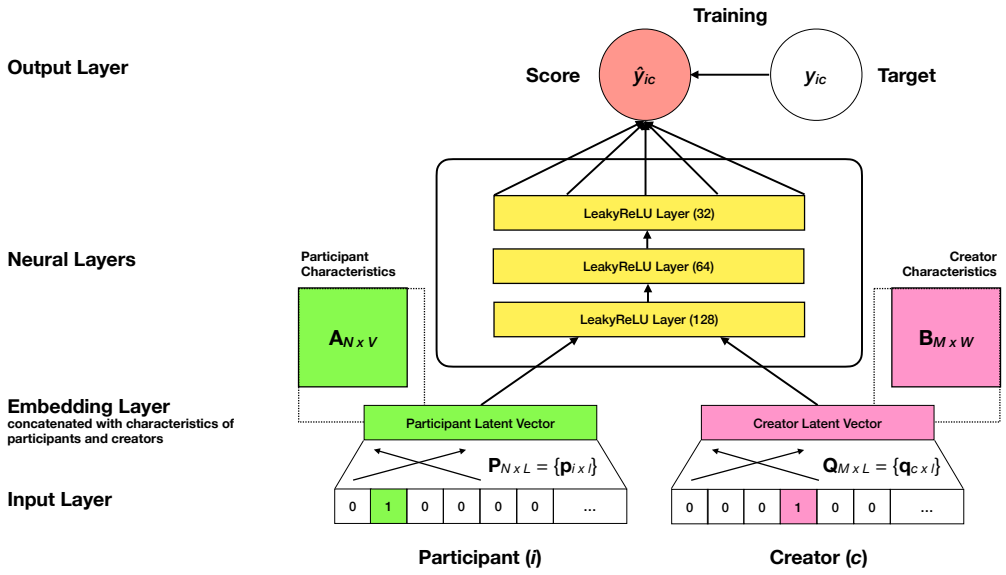
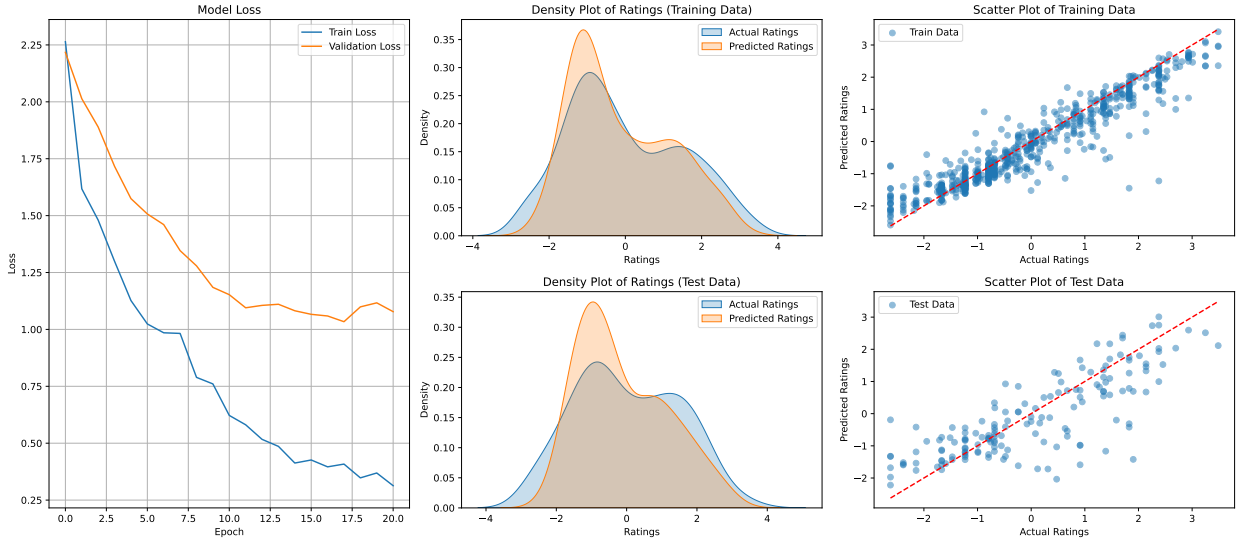


Figure A.2: Neural collaborative filtering model performance evaluation



A.2.4 Algorithm integration in the survey

The final version of the algorithm was deployed on the Google Cloud Computing platform using Cloud Run functions and Bucket functionality. We ran the Python 3.10 function with 1GB of allocated memory to process responses from participants in real time as they took the survey on Qualtrics. Activity logs indicate that while the algorithm successfully processed all participant

responses in the baseline survey, and recommendations were returned to be piped back into the Qualtrics survey, Qualtrics failed to pipe recommendations for 45 participants. These participants were dropped from the study. While the optimized version of the algorithm processed responses in an average of 0.006 seconds, the time it took for Qualtrics to pipe the responses could vary based on participants' internet connection quality, which could not be measured. Fortunately, very few participants dropped the survey due to this wait time.